Gender Inequality from a Spatial Perspective: Location Choice, Marriage Matching, and Labor Supply

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Abstract

In this paper, I build a structural model of location choices and marriage market matching under an imperfectly transferable utility framework. I emphasize that both the labor and marriage markets are local. With this model, we can open the black box of intra-household decisions and better understand the gender welfare gap beyond the gender wage gap. I find that the marriage market reduces the dispersion of the spatial distribution of highly skilled workers and can increase some workers' responsiveness to local wage shocks. Counterfactual analyses show that childcare subsidies financed by the labor income tax encourage people to move to locations that pay higher for their skills and increase the marriage rate and labor supply. Childcare subsidy increases aggregate social welfare and decreases the welfare gap by gender but increases the welfare gap by education.

Keywords: Marriage Matching, Location Choice, Female Labor Supply, Childcare Prices

JEL Codes: J12, J13, J18, J22, R23

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1 Introduction

As half the population, women are a mighty economic power that no society can afford to lose. Women's development is essential in both economic and political senses. Women have been catching up with men in education, employment, and wages in the last century, but the gap remains. The gender gap is closely related to a phenomenon called the "child penalty".

First, as pointed out by Cortés and Pan (2020), close to two-thirds of the overall gender earnings gap in the U.S. can be accounted for by the differential impacts of children on women and men. Second, the child penalty exhibits considerable geographic variation, as Kleven (2022) shows. Third, as a substitute for parental time, childcare from the market is too expensive. According to Child Care Aware[2], the national average price of child care was around $10.600 in 2021, comprising 10% of a married couple's family average income and 35% of a single parent's income. So child care is now an actively debated topic in the U.S. and is on the agenda of presidential candidates from both parties. The Tax Cuts and Jobs Act of 2017 doubled the tax credit to $2000 and made limits to the refundable amount of up to $1400 per child. The American Rescue Plan 2022 increased the Child Tax Credit from $2000 per child to $3600 for children under the age of 6 for working families.

One dollar in childcare subsidy can buy different amounts of childcare for two women living in two cities, leading to different incentives and marginal effects on female labor supply and welfare. According to Child Care Aware, there is a significant spatial variation in the affordability of child care. In Arkansas, the annual price of child care for an infant in a center is $7431 (9% of the median income of a married couple with children), while in Massachusetts, the number is $21,269 (15% of the median income of a married couple with children). With spatial variation in prices, we need a model incorporating people's decisions of location, marriage, and labor supply to understand gender inequality in wages, labor supply behaviors, and welfare.

So, to make further progress on gender equality, we need to investigate how location choices affect people's labor market prospects and intrahousehold decision-making. This paper builds a structural model to understand the gender gap from a spatial perspective, considering location

[2] https://www.childcareaware.org/catalyzing-growth-using-data-to-change-child-care/#ChildCareAffordability

choice, marriage matching, and labor supply. I emphasize that both the labor and marriage markets are local. When couples decide on consumption and labor supply, they make the decisions jointly and at the same location. In this way, endogenous choices of locations affect local marriage market conditions in a "supply-demand" framework, where demand (supply) means aggregate females' (males') choice probabilities of males (females). Each local marriage market reaches equilibrium when the "prices" in the marriage markets–the Pareto weight–adjust so that demand equals supply in each marriage market.

Since this model adopts a collective model with imperfectly transferable utility, we can't separate the labor supply decisions from the marriage market matching process: we can't separately estimate the preferences for work from location and marital choices since the unobservable Pareto weights enter the labor supply decisions of married couples. So, we must estimate preference parameters together with the equilibrium conditions in the marriage markets. Given parameters governing preferences, a unique vector of Pareto weights will clear the equilibrium constraints. This feature distinguishes this paper from previous research that we will review in the next section and makes the model suitable for analyzing gender inequality in a spatial framework.

With this model, we can open the black box of intra-household decisions and better understand the gender welfare gap beyond the gender wage gap. Besides, location choices based on the labor and marriage market enrich the intra-household decision-making model with important behavioral margins. With this model, I can perform counterfactual analysis to evaluate the effects of policies such as child-related transfers, holding the marriage market fixed or not. To illustrate the novelty of this model, I simulate the effects of a wage increase at each location on migration, holding the local marriage market condition fixed or not. In this way, we can see the role of marriage market consideration on migration decisions. Next, I simulate a series of childcare subsidy policies and find that childcare subsidies encourage people to move to locations that pay a higher wage for their skills, increase the marriage rate for all genders and education levels, and increase females' employment rate. Finally, I conduct a series of counterfactual policies focusing on welfare and inequality. I find that childcare subsidies financed by labor income tax can improve aggregate social welfare and decrease the welfare gap by gender but will increase the welfare gap by education level.

The rest of the paper proceeds as follows. Section 2 reviews relevant literature and discusses the similarities and differences between this paper and previous work. Section 3 describes the data and shows motivating facts. Section 4 lays out the structural model. Section 5 discusses identification and estimation techniques. Section 6 presents the estimates and model fit. Section 7 shows counterfactual analysis using the model estimates. Section 8 concludes.

2 Literature Review

For location choices, Rosen (1979) and Roback (1982) provide a canonical model and have inspired a series of quant spatial models, such as Diamond (2016). This strand of literature models heterogeneous workers' location considering wage and amenity and allows for heterogeneity in tastes and productivity and endogenous amenity, but the marriage market is ignored. For marriage matching, the seminal work by Choo and Siow (2006) started a market-level approach to understanding marriage matching patterns. When location choice is embedded into a marriage matching model, a marriage market will be naturally determined by the location choices of both males and females. On the other hand, a location choice will impact the type of spouse one is matched with because now the population structure is endogenous, and one's preference for a spouse will also affect which location to choose. So those two decisions are interlocked, thus rendering an equilibrium model of location choices and marriage matching necessary.

Though I follow the framework of Choo and Siow (2006), this paper differs in nontrivial ways: first, as in Chiappori, Dias and Meghir (2018) and Gayle and Shephard (2019), I model labor supply and household decisions, which directly micro-founded the value from marriage matching conditional on the equilibrium of the marriage market. Then we can avoid the just-identification property of Choo and Siow (2006), and the matching model allows us to recover the Pareto weights. Second, similar to Gayle and Shephard (2019) and Reynoso (2018), I consider an imperfectly transferable case so that the Pareto weights will affect the labor supply decisions of spouses. Third, the above literature doesn't model location choices, while the location is an essential choice variable in this Paper. In Chiappori, Dias and Meghir (2018), people make human capital investments considering its return from the marriage market. This paper doesn't model education decisions but how people choose locations to realize the returns from their human capital.

This paper also contributes to a recent but growing literature on the household and geography. Fan and Zou (2021) develop a spatial equilibrium model with endogenous marriage formation under perfectly transferable utility. Alonzo (2022) examines the effects of geographic heterogeneity in occupational returns on marriage market outcomes and the impact of family formation on the geographic allocation of labor. Barszczewski (2022) estimates a structural model of location choice which reflects immigrants' social integration by marrying natives. Moreno-Maldonado (2022) studies the interaction between city choice and labor supply in a unitary model. My paper differs from the above papers in several ways: first, labor supply is determined in a collective model with imperfectly transferable utility, so Pareto weights will not only affect each spouse's value from marriage but also affect joint labor supply; second, each location is allowed to differ in part-time work penalty; third, I introduce childcare and analyze counterfactual policies such as child-related transfers. We can perform more policy-relevant counterfactual analyses using an imperfectly transferable utility framework.

3 Data and Descriptive Evidence

The main data set I use for estimation is the American Community Survey (ACS) 2015-2019 5-year sample, which is large enough for estimating a model of location choice. ACS includes information such as current state of residence, birth state, gender, marital status, labor supply, income, etc. Childcare price data come from Child Care Aware 2018.

I put an age restriction of 25 to 45 so that people in my sample have finished their education and are still far from retirement. Also, I exclude couples of the same gender or cohabiting partners. I classify people into two educational categories: high education and low education. One is defined as having a high education if he or she has an education level of four years of college or above. I discretize labor supply into three categories: working full-time, working part-time, and not working. The data directly defines working or not, and I use 2000 annual working hours as the threshold for working full-time. In addition, I exclude observations that don't show exact birthplaces or are still in school. In general, my sample selection criteria are close to Gayle and Shephard (2019).

Table 1, Table 2, and Table 3 provide summary statistics for the full sample, female sample, and male sample, respectively. Females have surpassed males in college attainment: 41.6% females have received a college education, while the rate for males is 36.8%. But the average hourly wage is 35.4$ for males and 26.8$ for females, still a substantial gap. The gender gap also exists in labor supply: among males, 77.3% work full-time, 13.7% work part-time, and 9.0% don't work; among females, 51.6% work full-time, 29.1% work part-time, and 19.3% don't work. We can see that females still have a weaker tie with the labor market. When there is a wage or promotion penalty for working part-time, females are much more likely to suffer. Since education or skills are no longer able to explain the gender gap in either labor supply decisions or wage differences, jointly considering the labor market and the marriage market can help us go deeply into females' decisions.

There is substantial spatial variation in labor force participation for all genders and education levels. Figure 1 plots the density for state-level labor force participation rates by gender and education levels. Males with a college education are at nearly full employment across all locations, while males without a college education vary slightly in employment rate by location. However, female employment exhibits much greater variation across education groups and locations. These patterns motivate us to jointly model location choice and labor supply decisions to better understand gender inequality. Not surprisingly, wage also exhibits substantial spatial variation for each gender and education group, as shown in Figure 2. Workers with a college education have higher wages, but there is still a substantial gender gap in wage offers.

Next, we show that there is also spatial variation in the marriage market. For each gender and education level, the probability of getting married and marrying a spouse with a high education level varies with population vectors and varies across locations. Figure 3 shows state-level marriage rate by gender and education. Figure 4 shows the scatterplots of the probability of marrying a spouse of high education against the log skill ratio of the opposite sex, where the skill ratio is defined as the ratio of the population of people with high education to the population of people with low education. We can see that a state with a higher log skill ratio is associated with a higher probability of marrying a spouse with high education. This is not necessarily causal but indicates that the marriage market condition varies by location.

4 A Structural Model

To perform counterfactual analysis, I build a structural model that solves a two-stage maximization problem: in the first stage, a woman (man) will choose a location and a type of spouse [3] to match with to maximize expected utility; in the second stage, given marriage market outcomes and location choices, the woman (man) solves a problem of consumption and labor supply either independently (if single) or collectively with her (his) spouse (if married). Figure 5 shows a roadmap for the model. This model is static in nature, so it may miss people who have moved multiple times or who have moved and then returned home. But as shown by Kennan and Walker (2011), male movers move 1.98 times on average, and 50.2% of movers move back home. So for this model, ignoring repeated moves is not likely to introduce serious bias, especially when we are considering both the state of birth and current state of residence. Besides, this paper doesn't aim to explain high-frequency event such as yearly migration, then a static framework is a reasonable simplification.

4.1 Intra-household Decision Stage

We first discuss the second stage, which is a collective model. At this stage, uncertainty regarding wage offers, preference shocks, and fertility has been resolved. Consider E_f types of women, E_m types of men, and S locations in the economy. Types are defined as education categories and each location is a U.S. state. Each location differs in wage offers conditional on gender, education level, and full-time work status. Besides, locations differ in amenities and rents. We consider a very common specification of the utility function in spatial models:

$$u(c, l, h; s) = (1 - \beta)ln(c) + \beta lnh - \theta^{ls} l + A(\eta_s) + \epsilon^{ls}, \tag{1}$$

[3] She can also choose to remain single.

where c is consumption, h is housing, $l \in \{0, 0.5, 1\}$ indicates {No Work, Part-time Work, Full-time work}, $A(\eta_s)$ is amenity at location s, and ϵ^{ls} is choice-specific preference shock.

We assume that each household has a stochastic realization of fertility, especially whether there exists a kid under age 6. Fertility is stochastic but exogenously estimated from the data based on household characteristics. When there is a child under age 6 in the household, the household faces a fixed cost of full-time work. We assume that if the wife works full-time, then the household will pay a fixed cost x as specified below:

$$x = \mathbb{1}(l_f > 0.5) \cdot \mathbb{1}(HasKidsUnder6) \cdot (\theta_0^k + \theta_1^k log(p_s^k + 1)), \tag{2}$$

where p_s^k is the market price of childcare at location s. θ_0^k is the intercept of the fixed cost of full-time work when the childcare price is 0. θ_1^k is the coefficient indicating how the fixed cost of working changes with local childcare prices. We allow the intercept and coefficient to be different based on females' education level.

Next, we solve the problem of single people and married couples. A single woman i of type e_f living in location s will solve the below problem:

$$\begin{aligned}
&\max_{c,h,l} (1-\beta)ln(c) + \beta lnh - \theta_{e_f}^{ls} l - x + A_{e_f}(\eta_s, z_i) + \epsilon^{ls} \\
&s.t.\ c + r_s h = y_{e_f s} + w_{e_f s}(l) l \\
&\qquad x = \mathbb{1}(l_f > 0.5) \cdot \mathbb{1}(HasKidsUnder6) \cdot (\theta_{e_f,0}^k + \theta_{e_f,1}^k log(p_s^k + 1))
\end{aligned} \tag{3}$$

where r_s is the local rent. $A_{e_f}(\eta_s, z_i)$ is the amenity term which will be defined later. One thing to notice is that the wage offer depends on whether the worker works part-time or full-time to allow for nonlinear wage rates. Different locations have different distributions of occupations, which can lead to different part-time work penalties. Conditional on labor supply decisions, we can easily solve consumption and housing as:

$$c_{e_f s}(i) = (1-\beta)(y_{e_f s} + w_{e_f s}(l) l) \tag{4}$$

$$h_{e_f s}(i) = \beta \frac{(y_{e_f s} + w_{e_f s}(l) l)}{r_s} \tag{5}$$

Substitute equations (5) and (6) into equation (4), then the problem collapses into:

$$\max_{l} ln(y_{e_f s} + w_{e_f s}(l)l) - \theta^{ls}_{e_f} l - x + \epsilon^{ls} + [A_{e_f}(\eta_s, z_i) - \beta ln r_s] \tag{6}$$

Notice that the amenity term doesn't affect the labor supply decisions. This is an exclusion restriction: amenity affects location choices but doesn't affect labor supply directly. We specify the amenity term below:

$$A_{e_f}(\eta_s, z_i) = \theta^{bs}_{e_f}\mathbb{1}(s \in BirthState_i) + \theta^{a}_{e_f} a_s + \theta^{skill}_{e_f} log(\frac{pop_H}{pop_L}) \tag{7}$$

where $\mathbb{1}(s \in BirthState_i)$ indicates whether living outside of one's birth state and a_s is the local amenity index from Diamond (2016). Amenity is hard to measure, so we include the log skill ratio as a proxy for unmeasured amenities for each location[4]

Let σ^{ls}, σ^{w} be the parameters that characterize the distributions of work-specific preference shocks and wages. We can derive the expected value of a single woman i of type e_f living in location s as:

$$\begin{aligned} V^{f}_{e_f 0 s}(i) =& \mathbb{E}_{\epsilon^{ls}, w, HasKidsUnder6} \max_{l}\{ln(y_{e_f s} + w_{e_f s}(l)l) - \theta^{ls}_{e_f} l - x(l) + \epsilon^{ls}\} + \\ & [A_{e_f}(\eta_s, z_i) - \beta ln r_s] \\ =& \tilde{V}^{f}_{e_f 0 s}(\theta^{ls}_{e_f}, \sigma^{w}_{e_f s}, \sigma^{ls}) + [A_{e_f}(\eta_s, z_i) - \beta ln r_s] \end{aligned} \tag{8}$$

Thus we have solved the single women's problem. For single men, the problem is almost the same, the only difference is that men don't face a fixed cost of working. Next, we derive the married couple's expected value from the second stage. We assume that marriage doesn't affect people's preference for their own consumption. However, married people's utility is different from single people in three ways. First, married people's preference for leisure is dependent on his/her spouse's leisure. Specifically, the utility from work for females and females are specified as $-\theta^{ls}_{e_f} l_f + \theta^{comp}_{e_f} l_f l_m$ and $-\theta^{ls}_{e_m} l_f + \theta^{comp}_{e_m} l_f l_m$, where $\theta^{comp}_{e_f}$ and $\theta^{comp}_{e_m}$ capture the complementarity between leisure time of the wife and the husband. If $\theta^{comp}_{e_f}$ ($\theta^{comp}_{e_m}$) is positive, then the husband's

[4]An important finding from the literature is that local amenity responds to local population structure. Diamond (2016) specifies the supply of amenity as a linear function of log skill ratio.

(wife's) leisure is a complement to the wife's (husband's) leisure. Second, we allow for a stigma term for males if they earn less than their wives: $\theta_{e_m}^{stigma}\mathbb{1}(w_{e_f s}(l_f)l_f > w_{e_m s}(l_m)l_m)$. In Bertrand, Kamenica and Pan (2015), they find that there is an aversion to a situation where the wife earns more than her husband and this aversion impacts marriage formation, the wife's labor force participation, and marriage satisfaction. The stigma term is to capture the aversion and its impact on married people's labor supply. Third, we allow for a match quality to enter the utility of married couples.

A type $e_f e_m$ married couple ij at location s solve the below collective decision problem with Pareto weight $\lambda_{e_f e_m s}$ for woman:

$$\begin{aligned}
\max_{c_f,c_m,l_f,l_m,h} & \lambda_{e_f e_m s}[(1-\beta)ln(c_f) + \beta lnh - \theta_{e_f}^{ls} l_f - x + \theta_{e_f}^{comp} l_f l_m + \theta_{e_f e_m}^{match,f} + A_{e_f}(\eta_s, z_i) + \epsilon^{ls_i}] + \\
& (1-\lambda_{e_f e_m s})[(1-\beta)ln(c_m) + \beta lnh - \theta_{e_m}^{ls} l_m + \theta_{e_m}^{comp} l_f l_m - \theta_{e_m}^{stigma}\mathbb{1}(w_{e_f s}(l_f)l_f > w_{e_m s}(l_m)l_m) \\
& + \theta_{e_f e_m}^{match,m} + A_{e_m}(\eta_s, z_j) + \epsilon^{ls_j}] \\
s.t.\;\; & c_f + c_m + r_s h = y_{e_f s} + y_{e_m s} + w_{e_f s}(l_f)l_f + w_{e_m s}(l_m)l_m \\
& x = \mathbb{1}(l_f > 0.5)\cdot \mathbb{1}(HasKidsUnder6)\cdot(\theta_{e_f,0}^{k} + \theta_{e_f,1}^{k} log(p_s^k + 1))
\end{aligned} \tag{9}$$

Again, we first solve the spending problem conditional on joint labor supply:

$$c_f = \lambda_{e_f e_m s}(1-\beta)(y_{e_f s} + y_{e_m s} + w_{e_f s}(l_f)l_f + w_{e_m s}(l_f)l_m - x(l_f, l_m)) \tag{10}$$

$$c_m = (1-\lambda_{e_f e_m s})(1-\beta)(y_{e_f s} + y_{e_m s} + w_{e_f s}(l_f)l_f + w_{e_m s}(l_m)l_m - x(l_f, l_m)) \tag{11}$$

$$h = \beta\frac{(y_{e_f s} + y_{e_m s} + w_{e_f s}(l_f)l_f + w_{e_m s}(l_m)l_m - x(l_f, l_m))}{r_s} \tag{12}$$

Substitute equations (10), (11), and (12) into equation (9), then we transform the original problem to the below discrete choice problem of labor supply:

$$\begin{aligned}
\max_{l_f,l_m} & ln(y_{e_f s} + y_{e_m s} + w_{e_f s}(l_f)l_f + w_{e_m s}(l_m)l_m) - \lambda_{e_f e_m s}(\theta_{e_f}^{ls} l_f + x(l_f) - \theta_{e_f}^{comp} l_f l_m) \\
& - (1-\lambda_{e_f e_m s})(\theta_{e_m}^{ls} l_m + \theta_{e_m}^{stigma}\mathbb{1}(w_{e_f s}(l_f)l_f > w_{e_m s}(l_m)l_m) - \theta_{e_m}^{comp} l_f l_m) + \lambda\epsilon^{ls_i} + (1-\lambda)\epsilon^{ls_j} \\
& + [\lambda_{e_f e_m s}(\theta_{e_f e_m}^{match,f} + A_{e_f}(\eta_s, z_i)) + (1-\lambda_{e_f e_m s})(\theta_{e_f e_m}^{match,m} + A_{e_m}(\eta_s, z_j)) - \beta ln r_s]
\end{aligned} \tag{13}$$

It is obvious that labor supply will depend on the Pareto weight, and it is determined jointly. Besides, we allow for a match quality term that directly adds to the utility of both the husband and the wife. We use this term to capture assortative mating on education:

$$\begin{aligned}
\theta^{match,f}_{e_f e_m} &= \theta^{match,f}_0 \mathbb{1}(e_f = e_m = l) + \theta^{match,f}_1 \mathbb{1}(e_f > e_m) + \theta^{match,f}_2 \mathbb{1}(e_m > e_f) + \theta^{match,f}_3 \mathbb{1}(e_f = e_m = h) \\
\theta^{match,m}_{e_f e_m} &= \theta^{match,m}_0 \mathbb{1}(e_f = e_m = l) + \theta^{match,m}_1 \mathbb{1}(e_f > e_m) + \theta^{match,m}_2 \mathbb{1}(e_m > e_f) + \theta^{match,m}_3 \mathbb{1}(e_f = e_m = h)
\end{aligned} \tag{14}$$

We denote the expected value function for married women and men as:

$$V^f_{e_f e_m s}(i) = \tilde{V}^f_{e_f e_m s}(\theta^{ls}_{e_f}, \theta^{ls}_{e_m}, \theta^{match,f}_{e_f e_m}, \sigma^w_{e_f s}, \sigma^w_{e_m s}, \sigma^{ls_1}, \lambda_{e_f e_m s}) + A_{e_f}(\eta_s, z_i) - \beta lnr_s \tag{15}$$

$$V^m_{e_f e_m s}(j) = \tilde{V}^m_{e_f e_m s}(\theta^{ls}_{e_f}, \theta^{ls}_{e_m}, \theta^{match,m}_{e_f e_m}, \sigma^w_{e_f s}, \sigma^w_{e_m s}, \sigma^{ls_1}, \lambda_{e_f e_m s}) + A_{e_m}(\eta_s, z_j) - \beta lnr_s \tag{16}$$

4.2 Matching Stage

Now we consider the matching stage. Following Choo and Siow (2006), we assume that woman i will also have an idiosyncratic preference shock that is specific to herself and the type of spouse and location: $\epsilon^{ma}_{e_f e_m s}(i)$. Then Woman i with education e_f will choose a spouse and a location under the Pareto weights to solve the below problem:

$$\max_{e_m, s}\{V^f_{e_f e_m s}(i) + \epsilon^{ma}_{e_f e_m s}(i) | e_m \in E_m \cup \{0\},\ s \in S\} \tag{17}$$

Assume that $\epsilon^{ma}_{e_f e_m s}(i)$ follows i.i.d. type-I extreme value distribution with zero location and a scale parameter σ^{ma}. Then the choice probability for women i is:

$$p^f_{e_f e_m s}(i) = \frac{exp(\frac{V^f_{e_f e_m s}(i)}{\sigma^{ma}})}{\Sigma^S_{s'=1} \Sigma_{e'_m \in E_m \cup \{0\}} \exp\left(\frac{V^f_{e_f e'_m s'}(i)}{\sigma^{ma}}\right)}, \tag{18}$$

Similarly, we can derive the choice probability for men:

$$p^m_{e_f e_m s}(j) = \frac{exp(\frac{V^m_{e_f e_m s}(j)}{\sigma^{ma}})}{\Sigma^S_{s'=1}\Sigma_{e'_f \in E_f \cup \{0\}} \exp\left(\frac{V^m_{e'_f e_m s'}(j)}{\sigma^{ma}}\right)} \tag{19}$$

Denote the set of women of type e_f as $H^f_{e_f}$, $H^m_{e_m}$ for men. To reduce clutter, we denote Θ^f and Θ^m as the set of parameters for women and men. Aggregate over i and j, we can derive the "demand" and "supply" as:

$$D_{e_f e_m s}(\Theta^f, \Theta^m, \lambda_{e_f \cdot\cdot}) = \Sigma_{i \in H^f_{e_f}} p^f_{e_f e_m s}(i), \tag{20}$$

$$S_{e_f e_m s}(\Theta^f, \Theta^m, \lambda_{\cdot e_m \cdot}) = \Sigma_{j \in H^m_{e_m}} p^m_{e_f e_m s}(j), \tag{21}$$

Now, we can define the equilibrium in the marriage market.

Definition 1 (Equilibrium of the Marriage Market)**.** Equilibrium is achieved when for every (e_f, e_m, s) combination, the number of type e_m men demanded by type e_f women equals the number of type e_f men supplied to type e_m women at location s:

$$D_{e_f e_m s}(\Theta^f, \Theta^m, \lambda_{e_f \cdot\cdot}) = S_{e_f e_m s}(\Theta^f, \Theta^m, \lambda_{\cdot e_m \cdot}). \textit{for all } e_f,\ e_m, \textit{ and } s \tag{22}$$

We have two types of females, two types of males, and 51 locations. So, the above equation holds for 204 local marriage markets.[5] Given parameters Θ^f and Θ^m, the equilibrium constraints become a system of 204 equations with 204 Pareto weights. Interchangeably, the equilibrium constraints implicitly define a mapping from a vector of structural parameters to a vector of Pareto weights.

[5]Rigorously, we have 51 local marriage markets and each one has 4 sub-markets based on types of males and females. When there is no risk of confusion, a local marriage market means a marriage market at a specific location and for a specific combination of types.

5 Identification and Estimation

We have two sets of parameters to estimate. One is about the wage offers, and another is the structural parameters as listed in Table 4. Since we only observe wages when people work, ideally, we want to estimate the wage offers together with all the other parameters. But to make computation feasible, we take a two-step approach here: we first estimate wage offers, correcting for selection bias, and then we take the estimated wage offers as given and estimate the remaining parameters. The structural parameters fall into five categories: utility from working, match quality in marriage, costs from living outside one's birth state, utility from amenities, and parameters on the dispersion of preference shocks. Next, we first briefly discuss identification and then lay out the details of estimation techniques.

5.1 Identification

Parameters of wage equations are estimated separately, and identification is achieved using exclusion restrictions in the participation equation. β denotes the share of household expenditure on housing, which is taken directly from the data as 0.3, following Piyapromdee (2021). I estimate other parameters structurally, and below, I briefly discuss how the parameters can be identified. A rigorous proof of identification is included in Appendix B.

Parameters governing utility from working θ^l can be identified by observing single people's labor supply decisions. Parameters on the dispersion of shocks on labor supply can be identified because the coefficient in front of consumption has been normalized to 1. Thus the expected value of remaining single can be identified. We can identify Pareto weights Λ if there exists an exogenous force that changes the Pareto weights only through changing population distribution but not other components of the expected value of marriage, then Pareto weights can be identified as shown in Gayle and Shephard (2019). In this paper, migration costs and local amenities affect migration decisions, which in turn affect population structure, but don't directly affect intra-household decisions. So Pareto weights can be identified. Then we can identify the parameters on match quality and the scale parameter on preference shock by imposing the equilibrium condition in the marriage market and by observing choice frequency in the marriage market. For parameters governing migration θ^{bs}, consider a generic location s and two single people with the same gender and education but one was born in s while another was born outside of s. The difference in the choice probability of the two single people reveals the migration cost and thus helps identify θ^{bs}. Parameters of amenity can be identified by variation of the amenity across states.

5.2 Estimation

Estimation has two components. Wage equations and fertility are first estimated from the data. Other structural parameters and Pareto weights are estimated using indirect inference: minimizing the weighted distance between model moments and data moments with equilibrium constraints.

Each location has a menu of wage offers based on gender, education, and whether working part-time. Wage is assumed to be log-normal with the below specification

$$\begin{aligned} &lnW_i = \Sigma_{e,g,s}\mathbb{1}(e_i = e, g_i = g, s_i = s, l_i = pt) \cdot \delta_s^{e_g} + \epsilon_i \qquad (23) \\ &lnW_i \;\; \text{is observed iff i works} \end{aligned}$$

Selection into work is accounted for using Heckman (1979):

$$P(l_i = pt \; or \; ft) = \gamma Z_i + \eta_i \qquad (24)$$

I use the number of kids under age six as exclusion restrictions in the participation equation, assuming that the presence of kids affects participation decisions but not the wage offer from the labor market.

To estimate the structural parameters and Pareto weights, we solve the below constrained optimization problem:

$$Min \;\; (M(\Theta,\Lambda) - M_{data})^T W(M(\Theta,\Lambda) - M_{data})$$
$$s.t. \;\; ExcessDemand(\Theta,\Lambda) = 0, \tag{25}$$

where $M(\Theta,\Lambda)$ is the vector of moments simulated using the model, M_{data} is the empirical moments directly computed from the data, Θ is the vector of structural parameters, and Λ is the vector of Pareto weights for all the marriage markets. W is the weighting matrix, which is the inverse of the diagonal variance-covariance matrix of the empirical moments.[6] We choose the moments that are closely related to location choices, marital decisions, and labor supply. In Appendix x, we describe the moments in detail.

To estimate equation (25), we need to solve for the vector of Pareto weights given any trial value of structural parameters. So, we need to guarantee the existence and uniqueness of the Pareto Weights. This is true following the argument in Galichon, Kominers and Weber (2019).

Theorem 1 (Existence and Uniqueness of Pareto Weights)**.** *If the Excess Demand function satisfies the Gross Substitutability condition, then given any* Θ_0*, there exists a unique vector of* Λ *such that*

$$ExcessDemand(\Theta_0,\Lambda) = 0 \tag{26}$$

The proof from Galichon, Kominers and Weber (2019) is constructive, which also provides an algorithm to solve the Pareto weights: starting from Λ that are high enough, a Gauss-Seidel procedure will find a sequence of Λ that decreasingly converge to the unique value.

When Λ are all close to 1, the utility of a male in marriage is close to negative infinity, so males will remain single and the supply of males in the marriage market will become close to 0 while the demand of males by females will be positive. This means that every local marriage market will have positive excess demand. Now consider a Gauss-Seidel procedure where we solve the system of equations iteratively. For the first equation, we need to reduce the associated Pareto weight to clear this market since now we face a positive excess demand. Now take the

[6] The variance-covariance matrix of the empirical moments is computed with bootstrapping. Specifically, I generated 400 bootstrap samples with replacement.

updated first Pareto weight into the second equation and the second equation is still positive because of the Gross Substitutability condition: a worse price for females in the first market will (weakly) increase females' demand for the second market, so the second equation still faces a positive excess demand and we must reduce its Pareto weight as well. If we continue, then every Pareto weight will be reduced.

6 Estimation Results

6.1 Wage Offers

Figure 6 shows the mean log wage of full-time workers across locations for both genders and education levels. Not surprisingly, males with high education have the highest mean log wage, and next comes females with high education. Females with low education have the lowest mean log wages. In addition, there is substantial spatial variation in the mean log wages, which play an important role in affecting people's location choices.

In Figure 7, we see the part-time work penalty across locations for both genders and education levels. The part-time penalty is the difference in mean log wage between full-time and part-time work. We don't restrict the signs of the penalty, but they are estimated to be positive. So, earnings are a convex function of working time. The full-time/part-time margin per se can also contribute to gender inequality.

6.2 Structural Estimation

Table 5 shows the parameter estimates. Males (females) with higher education levels have smaller disutility from work than their lowly educated counterparts. The complementarity parameters are all significantly positive, indicating that couples' leisure time are compelements. The coefficients for the fixed cost of working full-time are estimated to be positive, which means a location with a higher childcare price puts a higher fixed cost of working full-time for females with young kids. The stigma terms are all positive, indicating that males incur a utility loss if their earnings are lower than their wives. Match quality parameter estimates indicate that people prefer to be matched with a spouse with the same education level. Males face a lower migrating cost than females and people with high education have a lower migrating cost than those with low education, which corresponds to the empirical patterns of migration observed in the data.

Figure 8 plots the Pareto weights across locations for each matching pattern and Table 6 provides a summary of the Pareto weights across locations. The Pareto weights exhibit geographic variation, especially for couples with different education levels. For the marriage pattern of highly educated wives and lowly educated husbands, the Pareto weights vary from 0.02 to 0.769. The spatial distribution of Pareto weights for other matching patterns are more centered.

6.3 Model Fit

Below, we show the model fit for key outcomes of the model. In Figure 9, I use the model estimates to predict people's choice probabilities of a spouse type: single, marrying a spouse of low education, marrying a spouse of high education. The prediction is made for each gender and each education, as shown in four sub-figures in Figure 9. Though the model slightly under-predicts highly-educated people's probability of marrying a highly-educated spouse, we can see that overall the fit is quite good.

Second, we want to see whether we can predict people's location choices with our model estimates. In Figure 10, we plot choice probabilities for all locations predicted by the model to that observed in the data. The prediction is also made for each gender and each education. Each dot represents a location, and the closer the dot is to the 45-degree line, the better the model fit. Though a few dots lie a little bit far, most dots are clustered around the 45-degree line, indicating the model estimates can reasonably replicate the observed location choices in the data.

Finally, we test the model fit on labor supply. We use the model estimates to predict labor supply conditional on gender, education, marital status, and whether having young kids (so $s \times 2 \times 3 \times 2 = 24$ groups). Figure 11 and Figure 12 display the results for males and female, respectively.The model accurately predicts females' probability of working status. For males, the model can accurately predict employment rate but under-predict the probability of working full-time for some subgroups.

7 Counterfactual Analyses

7.1 The Role of Marriage Market

To understand the role of marriage market consideration in migration decisions, we conduct two sets of counterfactual analyses. First, we simulate population distribution by shutting down the marriage market consideration. In this scenario, people make location choices based on the expected value of being single: $V^f_{e_f 0 s}$ for females of education type e_f, and $V^m_{0 e_m s}$ for males of education type e_m. Second, we simulate the elasticity of location choices with respect to wages with or without achieving equilibrium in the marriage market. The elasticity of migration with respect to wage shocks is key to determining the incidence of local shocks and our model shows novel patterns of elasticities with the marriage market consideration. The purpose of these exercises is to show that both labor market and marriage market considerations are important behavioral margins. This will help us understand the counterfactual analyses we conduct later.

7.1.1 Marriage Market Consideration on Spatial Inequality

By manually setting the match quality parameter to negative infinity, no one will choose to get married and we rule out the marriage market consideration. We simulate population distribution under this scenario and compare it with the baseline model. We focus on how the marriage market affects the geographic sorting of highly educated workers. To answer this question, we compute the proportion of highly educated workers (skill ratio) for each location under the baseline model and the counterfactual. Table 7 shows the results. The mean skill ratio for the baseline model and the counterfactual are almost the same, but the standard deviations differ. When the marriage market is excluded, the standard deviation of skill ratios becomes larger, which means the marriage market helps decrease the geographic sorting of skills. This is consistent with the findings from Fan and Zou (2021) that marriage is a dispersion force. I have also computed skill ratios for male and female samples, and the patterns are the same.

The economic intuition behind this is that the marginal return from the marriage market is diminishing as "supply" in the marriage market increases. When we exclude the marriage market, people make location choices based on the expected value of being single, which is independent of the supply and demand conditions in the local marriage market. A location with higher wages for highly educated males will attract more highly educated males, which in turn will increase the supply of highly educated males in the marriage market. The return from the marriage market will decrease, which dampens the effect when we only consider the labor market.

7.1.2 The Role of Marriage Market on Migration

For each state, gender, and education level, we increase the skill price by 10%[7], and simulate the changes in population. Then we compute the elasticity of location choice with respect to the wage increase.

$$Elasticity\ of\ Location\ Choice_j^{e_g} = \frac{dlog(probability_j^{e_g})}{0.1} \tag{27}$$

where j indicates a state and e_g indicates a demographic group (defined by gender and education). The elasticity of migration with respect to wage shocks is also estimated in Kennan and Walker (2011) and Anstreicher (2021). This elasticity shows how responsive people are to wage shocks. But in this model, when people are attracted to a location due to wage shocks, the local population structure will also be affected, which will in turn affect the marriage market. To quantify the role of the marriage market on migration, we simulate two sets of migration elasticities. First, we simulate the elasticity of migration with respect to wage shocks holding the Pareto weights as in the baseline estimation results, so we ignore the effects of population changes on the marriage market, and the marriage market in this counterfactual is not in equilibrium. Second, we require that the marriage market must also be in equilibrium after the wage shocks. By comparing the migration elasticity simulated in the two scenarios, we can see how the marriage market affects migration decisions.

Figure 13 displays the results of the above exercise. The x-axis shows the elasticity of

[7]To provide a real-world example, the fracking boom is estimated to have increased wages by 5.4 – 11.0% in communities that fracked, see Bartik et al. (2019).

migration with respect to wage shocks with Pareto weights fixed, while the y-axis shows the elasticity with Pareto weights having been updated. The discrepancy between the scatter plot and the 45-degree line indicates the role of the marriage market on migration. If location A experiences a wage increase for a demographic group, say, highly-educated males, then keeping the Pareto weights fixed, highly-educated males will be attracted to location A because the returns from the labor market are higher now. But the marriage market will also change for subsequent reasons: now location A has more highly-educated males than before due to the wage shock; because highly-educated males at location A have a higher wage now, they will become more desirable to females at location A and all other locations; hence population structure at location A will change and the "price" of the marriage market will adjust to reestablish equilibrium. The change in the marriage market is the reason why the elasticity of migration with respect to wage shocks will be different depending on whether we update the Pareto weights.

The scatter plots for highly educated females lie closer to the 45-degree line than all other demographic groups. For highly educated males, the scatter plot is not as tight as its female counterpart. For highly educated people, some locations have a higher elasticity of migration with respect to wage shocks when Pareto weights are held fixed. This means that marriage market consideration might dampen the effect of wage shocks on migration. On the contrary, the scatter plots for lowly educated people lie above the 45-degree line, which means marriage market considerations amplify their migration responses to wage shocks. Ignoring the marriage market, highly educated people have a higher migration elasticity than lowly educated people. But once the marriage market is considered, the gap will shrink. For females, half of the gap in elasticity is eliminated once we update the Pareto weights, changing from 0.07 to 0.035. In the real world, we expect the marriage market to adjust at a low frequency. So, if we only look at the data, the elasticity we can compute may or may not reflect the marriage market adjustment. A model that explicitly considers both the labor market and the marriage market can offer both "short-run" and "long-run" estimates of migration elasticity. As online dating becomes more and more popular, and the rise of remote work, I expect that marriage market consideration will play a more important role in migration decisions in the future.

7.2 Childcare Subsidy

Now, we consider a series of counterfactuals with respect to childcare costs. We are interested to know how marriage decisions, location choices, and labor supply decisions would be affected. There are substantial spatial differences in wage offers for each gender and education level. But people may not always move to the places with the best opportunities. Childcare burden can be a possible reason: if raising a child is so costly that one can't work even if moved to such a place, then this person may choose a place with a lower wage offer. Then, a natural question is: Will a childcare subsidy help people choose locations that pay higher wages for their skills, especially for those lowly-educated females? If a childcare subsidy encourages women to move to locations that pay more for their skills, then gender inequality will decrease as a result. In addition, through the marriage market mechanism, the location choices of males might also change. The model we estimate in this paper allows for a comprehensive evaluation of the effects of childcare subsidies.

Specifically, we change the childcare price at each location as:

$$\bar{p}_s^k = (1-\tau) \times (p_s^k - minimum(p_{s'}^k)) + minimum(p_{s'}^k), \tag{28}$$

So, for each dollar the childcare price is above the lowest price in the U.S., the government will subsidize with τ dollar. We simulate the value of τ from 0.05 to 1.0, with 0.05 as the step size. So we simulate 20 childcare subsidy rates. The government needs to collect taxes to finance the childcare subsidy. We consider two types of taxes: a lump-sum tax and a labor income tax. For each level of childcare subsidy, we simulate the government expenditure and tax revenue and set the lump-sum tax or labor income tax rate so that the government expenditure equals the tax revenue. So our simulation has taken into consideration people's behavioral responses to government policies.

We focus on three sets of outcomes: location choices, marriage decisions, and labor supply. For location choices, we are interested to know whether a childcare subsidy will encourage people to move to locations that pay higher for their human capital. For marriage decisions, we are interested to know how childcare subsidy affects people's choice probabilities of each marital status. For labor supply decisions, we simulate people's choice probabilities of working and full-time working.

Figure 14 plots the population increasing rate against the mean log wage for each location under a 100% subsidy rate financed by the lump-sum tax, and Figure 15 plots the one that is financed by labor income tax. [8] We can see that for the lump-sum tax version, the population-increasing rate is positively correlated with the mean log wage: a location with a higher mean wage will experience a larger population increase. For the labor income version, the correlation between population increase and mean log wage is much weaker. This is not surprising since the introduction of the labor income tax will reduce people's incentives to work, which in turn reduces people's motivation to relocate due to the labor market consideration.

Next, we examine how marital outcomes change due to the childcare subsidy. Figure 16 and Figure 17 plot the choice probability of being single against the childcare subsidy rate for each gender and education level, financed by the lump-sum tax and labor income tax. We can see that for both financing methods, for both genders and education levels, people's probability of being single decreases monotonically as the childcare subsidy rate increases. The childcare subsidy decreases females' fixed cost of working full-time, which increases females' position in both the labor market and the marriage market. So it is not surprising that more females choose to get married. For males, now it is more profitable to get married because the female population has a higher earning potential with the childcare subsidy. Figure 18 and Figure 19 show the results of marrying a highly educated spouse. The patterns are the same: people now are more likely to marry a highly educated spouse because more people choose to get married. However, the magnitude is much smaller due to the adjustment of Pareto weights.

Last, we investigate how labor supply responds to childcare subsidies. For each gender, education level, presence of young kids, and level of childcare subsidy rate, we simulate people's probabilities of not working, part-time work, and full-time work. Figure 20 and Figure 21 plot the choice probability of working against the childcare subsidy rate for each gender and education level, respectively financed by the lump-sum tax and labor income tax. We can see that the effect of childcare subsidies varies by gender, education, presence of young kids, and

[8] For other levels of subsidies, the results are qualitatively the same but with a smaller magnitude.

financing methods. First, the probability of working for females with young kids increases with the childcare subsidy rate but the magnitude is much larger under the lump-sum tax for lowly educated females. This is reasonable since the labor income tax has a negative impact on people's labor supply while the lump-sum tax can increase labor supply through the income effect. The probability of working for highly educated females also increases but in a smaller magnitude than their lowly educated counterparts. The probability of males slightly increases in the lump-sum tax scenario while decreases in the income tax scenario. Figure 22 and Figure 23 show the results for the probability of working full-time. The patterns are similar except that highly educated females' probability of working full-time increases greatly with the subsidy rate. With a 100% childcare subsidy, the probability of working full-time for highly educated females increases from 55% to 70%.

7.3 Inequality and Welfare Analysis

We have shown the effects of childcare subsidies on location choices, marriage decisions, and labor supply. Now we focus on welfare analysis. Here we define welfare as the weighted expected value conditional on gender and education level, where the weights are population distribution by birth state. Specifically, we define the aggregate welfare of females and males as:

$$Welfare^{e_f} = \Sigma_{bs} \frac{pop^{e_f}(bs)}{pop^{e_f}} \mathbb{E}_{\epsilon^{ma}_{e_f e_m s}} max_{e_m,s}\{V^f_{e_f e_m s}(bs) + \epsilon^{ma}_{e_f e_m s}\} \tag{29}$$

$$Welfare^{e_m} = \Sigma_{bs} \frac{pop^{e_m}(bs)}{pop^{e_m}} \mathbb{E}_{\epsilon^{ma}_{e_f e_m s}} max_{e_f,s}\{V^m_{e_f e_m s}(bs) + \epsilon^{ma}_{e_f e_m s}\} \tag{30}$$

where $V^f_{e_f e_m s}(bs)$ is the expected value of a female whose birth state is bs and has an education level e_f choosing location s and a marital status e_m (can be single as well), and $\frac{pop^{e_f}(bs)}{pop^{e_f}}$ is the share of females with education e_f whose birth state is bs. $\mathbb{E}_{\epsilon^{ma}_{e_f e_m s}} max_{e_m,s}\{V^f_{e_f e_m s}(bs) + \epsilon^{ma}_{e_f e_m s}\}$ and $\mathbb{E}_{\epsilon^{ma}_{e_f e_m s}} max_{e_f,s}\{V^m_{e_f e_m s}(bs) + \epsilon^{ma}_{e_f e_m s}\}$ are the social surplus functions as in McFadden (1981). Because of the migration cost, even people with the same gender and education will have different expected values, so we aggregate the welfare with population distribution at birth as weights.

First, we show the aggregate welfare under the childcare subsidy policies we have simulated before. Figure 24 shows the results under the lump-sum tax while Figure 25 shows the results under the labor income tax. When the childcare subsidy is financed by a lump-sum tax, the welfare impacts display a conflict of interest between people of different education levels. welfare of highly-educated males and females increases with the subsidy rate while the welfare of lowly-educated males and females decreases with the subsidy rate. So we can't find a subsidy rate that benefits people from all education levels. When the childcare subsidy is financed by the labor income tax, the welfare of highly educated males and females still increases with the subsidy rate. However, the welfare of lowly educated females exhibits a u-shaped relationship with the subsidy rate: the welfare will decrease until the subsidy rate reaches 0.3, and will increase after that. The welfare of lowly educated males monotonically decreases with the subsidy rate. For both financing methods, we can't find a Pareto-improving subsidy policy.

There are three effects that drive the welfare results we see. First, the childcare subsidy benefits the females by providing insurance. If a female has kids, then she will face the cost of working full-time. The childcare subsidy together with tax helps move resources between the state of having no kids and the state of having kids. Highly educated females benefit more than lowly educated females from this insurance mechanism since highly educated females lose more by working less. [9] Second, the tax will decrease decrease people's welfare. The lump-sum tax is equally shared by everyone while the labor income tax comes more from those who earn higher earnings, i.e., the highly educated people. This explains why the welfare of lowly educated females decreases with the subsidy under the lump-sum tax while eventually increases under the labor income tax. Third, through the location and marriage channels, the welfare of everyone can be affected. As we have shown before, both males and females will make different location and marital decisions under the childcare subsidy. The first effect has no impact on males, the second effect affects males' welfare negatively, while the effect can benefit the males. Because highly educated males benefit more from the marriage market, we observe the diverging pattern of males of different education levels.

Suppose the social planner puts equal weight on everyone, then we can aggregate the female

[9] Highly educated females have higher wage offers and lower disutility from working.

welfare and male welfare of different education levels into the aggregate social welfare. In addition, we also care about the relative welfare by gender and education. We define the relative welfare of females to males as:

$$\frac{Welfare^f}{Welfare^m}, \tag{31}$$

and we define the relative welfare of lowly educated people to highly educated people:

$$\frac{Welfare^H}{Welfare^L}. \tag{32}$$

If the relative welfare is smaller than 1, then there is a gender or education gap in welfare. The smaller the number, the larger the gap.

Figure 26 shows the aggregate social welfare, relative welfare by gender, and relative welfare by education under various childcare subsidy rates. If the childcare subsidy is financed by the lump-sum tax, then aggregate welfare will decrease, while both the gender welfare gap and education welfare gap will increase. So the childcare subsidy financed by a lump-sum tax will not just decrease aggregate social welfare but also increase inequality by gender and education. When the childcare subsidy is financed by a labor income tax, aggregate social welfare increases, the gender welfare gap decreases while the education welfare gap increases.

Last, we consider three counterfactual scenarios that might affect aggregate welfare or welfare gaps. First, we take out the fixed cost of working full-time for females by setting the relevant parameters to zero. Second, we remove the stigma term for males so earning less than their wives won't incur a stigma. Third, we set wage offers for females to males of the same education level. We call the three scenarios "No Fixed Cost", "No Stigma", and "Wage Equalization". For each scenario, we simulate two sets of counterfactual: for the first one, we keep the Pareto weights as in the baseline model; for the second one, we update the Pareto weights to make sure the marriage markets are in equilibrium.

Figure 27 shows the results for the above exercise. We can see that the welfare implications vary depending on whether we consider the marriage market equilibrium, especially for the "No Stigma" scenario. When Pareto weights are held fixed as in the baseline model, aggregate welfare for the "No Stigma" scenario increases from 8.440 to 8.616, but the relative welfare by gender decreases from 0.889 to 0.846, and the relative welfare by education decreases from 0.814 to 0.811. We will draw the conclusion that taking out stigma is welfare-improving at the cost of increasing inequality by gender and education. However, when we update the Pareto weights so that the marriage markets are in equilibrium, then the welfare improvement will be smaller, but the relative welfare by gender will be almost the same as in the baseline results, and the relative welfare by education will be larger than in the baseline model. Then we can draw the conclusion that taking out stigma is not only improving aggregate welfare but also reducing inequality. This illustrates the importance of considering the marriage market equilibrium when we conduct welfare analysis. This exercise also tells us that if the society has a more egalitarian social norm so that men don't have to be the bread-winner, then both males and females can benefit.

8 Discussion and Conclusion

This paper extends the Choo and Siow (2006) marriage matching framework to a spatial setting, shedding light on how location choices are affected by local labor and marriage markets, and how location choices affect local marriage market conditions and intra-household decision-making. In Chiappori, Dias and Meghir (2018), people make human capital investment decisions taking into account how their future marriage market prospects would be affected. This paper complements Chiappori, Dias and Meghir (2018) in the sense that, people's location choices will affect the marriage market they face. The results in this paper show that the marriage market plays an important role in people's migration decisions, and can generate novel predictions. In policy simulations, we find that childcare subsidies encourage people to migrate to locations that pay higher prices for their skills, increase marriage rate and labor supply. If we finance the childcare subsidy by the labor income tax, then we can increase the social aggregate welfare and decrease the gender welfare gap but at the cost of increasing education welfare gap.

This paper has three major limitations. First, the wage offer doesn't consider the idiosyncratic match quality between individuals and locations for tractability issues. To implement the Choo and Siow (2006) market-level approach in marriage matching, the types of males and females are discrete and can't be too large for computational considerations. [10] Second, the model takes a partial equilibrium stance on the labor market, ignoring externalities that might be brought by inflows of highly educated people. However, the marriage market takes a general equilibrium stance since we allow the Pareto weights to change in response to changes in local population structures. Third, the model is static and doesn't consider repeated moves. This is due to both data considerations [11] and computational tractability. It is better to interpret the model as depicting a snapshot of a long-run equilibrium.

Extensions that take a full general equilibrium in both the labor and marriage market or allow for individual heterogeneity in match quality will be fruitful. According to the question at hand, extending the model to a dynamic one can also be crucial. But they are beyond the scope of this paper and I leave those extensions for future research.

[10]The number of marriage markets is the multiplication of the number of types for men, number of types for women, and number of locations.

[11]Estimating a location choice model requires a large sample, especially when there are many locations and types of people. Census or ACS data are large in sample size but are cross-sectional, while panel data are much smaller in sample size. My model can be easily extended to MSA level instead of the state level. I use state as a location because childcare price is only available at the state level.

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A Tables and Figures

A.1 Tables

Table 1: Summary Statistics for the Full Sample

Statistic	N	Mean	St. Dev.	Min	Max
Male	3,382,553	0.486	0.500	0	1
With High Education	3,382,553	0.393	0.488	0	1
Married	3,382,553	0.630	0.483	0	1
Working Full-time	3,382,553	0.641	0.480	0	1
Working Part-time	3,382,553	0.217	0.412	0	1
Not Working	3,382,553	0.143	0.350	0	1
Hourly Wage	2,899,348	31.236	31.302	0.001	523.170
Nonlabor Income	3,382,553	3,560.148	2,221.394	1,596.722	7,956.686
Log Rent	51	9.502	0.253	8.999	10.067
Childcare Price in Centers (Age 4)	51	8,989.209	2,159.552	4,670.000	14,736.000
Amenity	51	1.004	0.626	−0.670	4.715

Notes: Male is a binary variable indicating whether a person is male. A person is defined as "with high education" if he or she has an education of 4 years of college or above. A person is defined as working full-time if annual working hours in the last year are equal to or above 2000 hours; a person is defined as working part-time if he or she has positive weeks of work in the last year but annual working hours are below 2000; a person is defined as not working if he or she has zero weeks of work in the last year. Hourly wage is defined as the ratio of earnings income to annual working hours. Nonlabor income is the sum of business income, investment income, and other non-wage income. Rent is the grossly annual rental cost of a housing unit, including contract rent plus additional costs of utilities. I adjust for the number of people in a household and aggregate to the state level to represent the living cost of each location. All the above information comes from ACS 2015-2019. Childcare prices in centers for Age 4 come from Child Care Aware's "State Fact Sheets of 2018". Amenity is an index constructed by Diamond (2016), which is the first principle component extracted from variables for the retail environment, transportation infrastructure, crime, environmental quality, school quality, and job quality (beyond wages).

Table 2: Summary Statistics for the Female Sample

Statistic	N	Mean	St. Dev.	Min	Max
With High Education	1,740,199	0.416	0.493	0	1
Married	1,740,199	0.611	0.488	0	1
Working Full-time	1,740,199	0.516	0.500	0	1
Working Part-time	1,740,199	0.291	0.454	0	1
Not Working	1,740,199	0.193	0.395	0	1
Hourly Wage	1,404,331	26.834	26.437	0.001	523.170
Nonlabor Income	1,740,199	2,602.573	1,192.040	1,596.722	4,015.266

Notes: A person is defined as "with high education" if he or she has an education of 4 years of college or above. A person is defined as working full-time if annual working hours in the last year are equal to or above 2000 hours; a person is defined as working part-time if he or she has positive weeks of work in the last year but annual working hours are below 2000; a person is defined as not working if he or she has zero weeks of work in the last year. Hourly wage is defined as the ratio of earnings income to annual working hours. Nonlabor income is the sum of business income, investment income, and other non-wage income.

Table 3: Summary Statistics for the Male Sample

Statistic	N	Mean	St. Dev.	Min	Max
With High Education	1,642,354	0.368	0.482	0	1
Married	1,642,354	0.650	0.477	0	1
Working Full-time	1,642,354	0.773	0.419	0	1
Working Part-time	1,642,354	0.137	0.344	0	1
Not Working	1,642,354	0.090	0.286	0	1
Hourly Wage	1,495,017	35.372	34.761	0.001	523.077
Nonlabor Income	1,642,354	4,574.772	2,580.021	2,606.506	7,956.686

Notes: A person is defined as "with high education" if he or she has an education of 4 years of college or above. A person is defined as working full-time if annual working hours in the last year are equal to or above 2000 hours; a person is defined as working part-time if he or she has positive weeks of work in the last year but annual working hours are below 2000; a person is defined as not working if he or she has zero weeks of work in the last year. Hourly wage is defined as the ratio of earnings income to annual working hours. Nonlabor income is the sum of business income, investment income, and other non-wage income.

Table 4: Notation and Meaning of Structural Parameters

	Notation		Notation
(Dis)utility from work: θ^{ls}		Complementarity in Leisure for Couples: θ^{comp}	
Female, low education	$\theta^{ls}_{low,female}$	Female, low education	$\theta^{comp}_{low,female}$
Female,high education	$\theta^{ls}_{high,female}$	Female, high education	$\theta^{comp}_{high,female}$
Male, low education	$\theta^{ls}_{low,male}$	Male, low education	$\theta^{comp}_{low,male}$
Male, high education	$\theta^{ls}_{high,male}$	Male, high education	$\theta^{comp}_{high,male}$
Fixed Cost of Full-time Work for Females: θ^{k}		Stigma from Earning Less for Males: θ^{stigma}	
Low Education,intercept	$\theta^{k}_{0,low}$	Low education	θ^{stigma}_{low}
Low Education, coefficient	$\theta^{1,low}$	High education	θ^{stigma}_{high}
High Education, intercept	$\theta^{k}_{0,high}$		
High Education, coefficient	$\theta^{k}_{1,high}$		
Match quality for Females: $\theta^{match,f}$		Utility from local amenity: θ^{a}	
$e_f = e_m = L$	$\theta^{match,f}_{0}$	Female with low education	$\theta^{a}_{low,female}$
$e_f > e_m$	$\theta^{match,f}_{1}$	Female with high education	$\theta^{a}_{high,female}$
$e_f < e_m$	$\theta^{match,f}_{2}$	Male with low education	$\theta^{a}_{lowmale}$
$e_f = e_m = H$	$\theta^{match,f}_{3}$	Male with high education	$\theta^{a}_{high,male}$
Match quality for Males: $\theta^{match,m}$		Utility from local skill ratio: θ^{skill}	
$e_f = e_m = L$	$\theta^{match,m}_{0}$	Female with low education	$\theta^{skill}_{low,female}$
$e_f > e_m$	$\theta^{match,m}_{1}$	Female with high education	$\theta^{skill}_{high,female}$
$e_f < e_m$	$\theta^{match,m}_{2}$	Male with low education	$\theta^{skill}_{low,male}$
$e_f = e_m = H$	$\theta^{match,m}_{3}$	Male with high education	$\theta^{skill}_{high,male}$
Cost from migration:θ^{bs}		Dispersion parameters of Shocks:	
Female with low education	$\theta^{bs}_{low,female}$	Work-specific for female	σ^{ls_f}
Female with high education	$\theta^{bs}_{high,female}$	Work-specific for male	σ^{ls_m}
Male with low education	$\theta^{bs}_{low,male}$	Marital shock	σ^{ma}
Male with high education	$\theta^{bs}_{high,male}$		

Notes: This table shows notations for structural parameters.

Table 5: Structural Parameter Estimates

	Estimate	Standard Error		Estimate	Standard Error
(Dis)utility from work: θ^{ls}			Complementarity in Leisure for Couples: θ^{comp}		
Female, low education	0.548	0.0003	Female, low education	0.011	0.0007
Female,high education	0.431	0.0009	Female, high education	0.044	0.0003
Male, low education	0.521	0.0003	Male, low education	0.076	0.0010
Male, high education	0.364	0.0019	Male, high education	0.082	0.0012
Fixed Cost of Full-time Work for Females: θ^{k}			Stigma from Earning Less for Males: θ^{stigma}		
Low Education,intercept	-1.669	0.2440	Low education	1.210	0.0067
Low Education, coefficient	0.232	0.0268	High education	2.374	0.0283
High Education, intercept	-5.849	0.2994			
High Education, coefficient	0.662	0.0329			
Match quality for Females: $\theta^{match,f}$			Utility from local amenity: θ^{a}		
$e_f = e_m = L$	-1.853	0.0306	Female with low education	0.006	0.0013
$e_f > e_m$	-3.060	0.0120	Female with high education	0.105	0.0019
$e_f < e_m$	-5.362	0.0274	Male with low education	0.023	0.0013
$e_f = e_m = H$	-2.715	0.0219	Male with high education	0.193	0.0030
Match quality for Males: $\theta^{match,m}$			Utility from local skill ratio: θ^{skill}		
$e_f = e_m = L$	-2.523	0.0393	Female with low education	-0.807	0.0154
$e_f > e_m$	-5.396	0.0746	Female with high education	0.519	0.0075
$e_f < e_m$	-3.147	0.0465	Male with low education	-1.200	0.0202
$e_f = e_m = H$	-1.325	0.0443	Male with high education	0.854	0.0130
Cost from migration:θ^{bs}			Dispersion parameters of Shocks:		
Female with low education	9.523	0.1367	Work-specific for female	0.439	0.0009
Female with high education	8.570	0.1240	Work-specific for male	0.421	0.0011
Male with low education	9.210	0.1329	Marital shock	1.820	0.0262
Male with high education	7.466	0.1090			

Notes: This table shows estimates and standard errors for structural parameters. Standard errors are computed using the formula in Gourieroux, Monfort and Renault (1993)

Table 6: Pareto Weight Distribution

		Males	
		Low Education	High Education
Females	Low Education	0.578	0.610
		[0.559, 0.594]	[0.581, 0.700]
	High Education	0.532	0.842
		[0.020, 0.769]	[0.810, 0.905]

Notes: The table shows the distribution of Pareto weights from our estimated model. The unbracketed numbers correspond to the average weight across markets (weighted by population size) within an (e_f, e_m) *match. The range in brackets provides the range of values that we estimate across markets.*

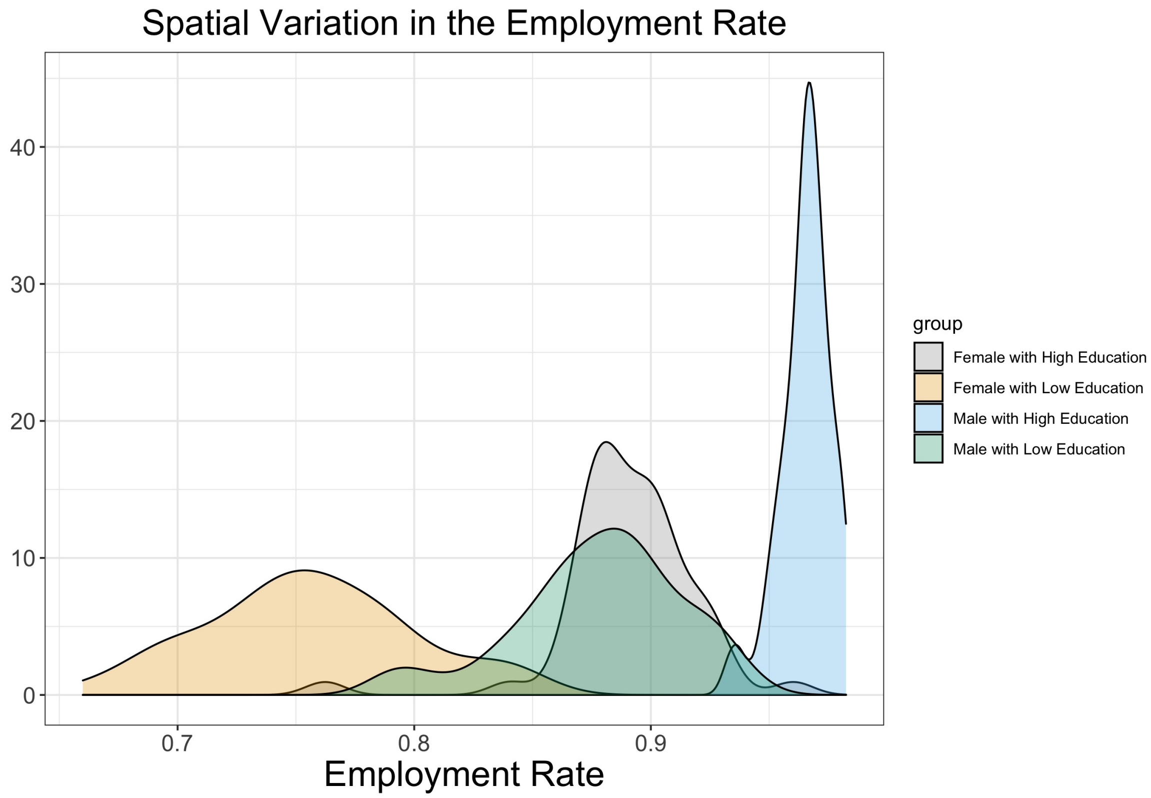
Table 7: Skill Ratio Across Locations

	Skill Ratio		**Skill Ratio (Female)**		**Skill Ratio (Male)**	
	Baseline	Marriage Excluded	Baseline	Marriage Excluded	Baseline	Marriage Excluded
Mean	0.400	0.403	0.423	0.423	0.377	0.383
S. D.	0.079	0.093	0.070	0.076	0.088	0.112
C. V.	0.196	0.230	0.166	0.181	0.234	0.292

Notes: this table compares the skill ratio distribution in the baseline model and the counterfactual where the marriage market is excluded. C.V. stands for coefficient of variation, which is the ratio of standard deviation to mean.

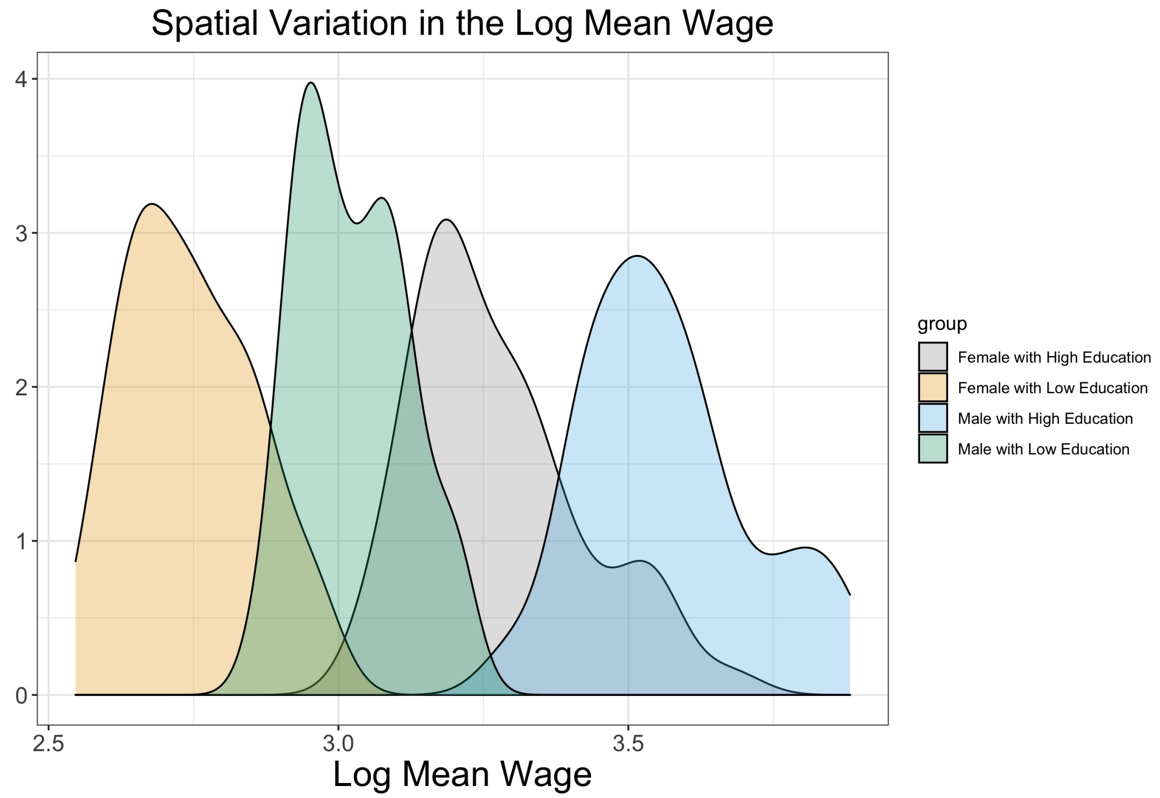
A.2 Figures

Figure 1: Spatial Variation in Employment Rate



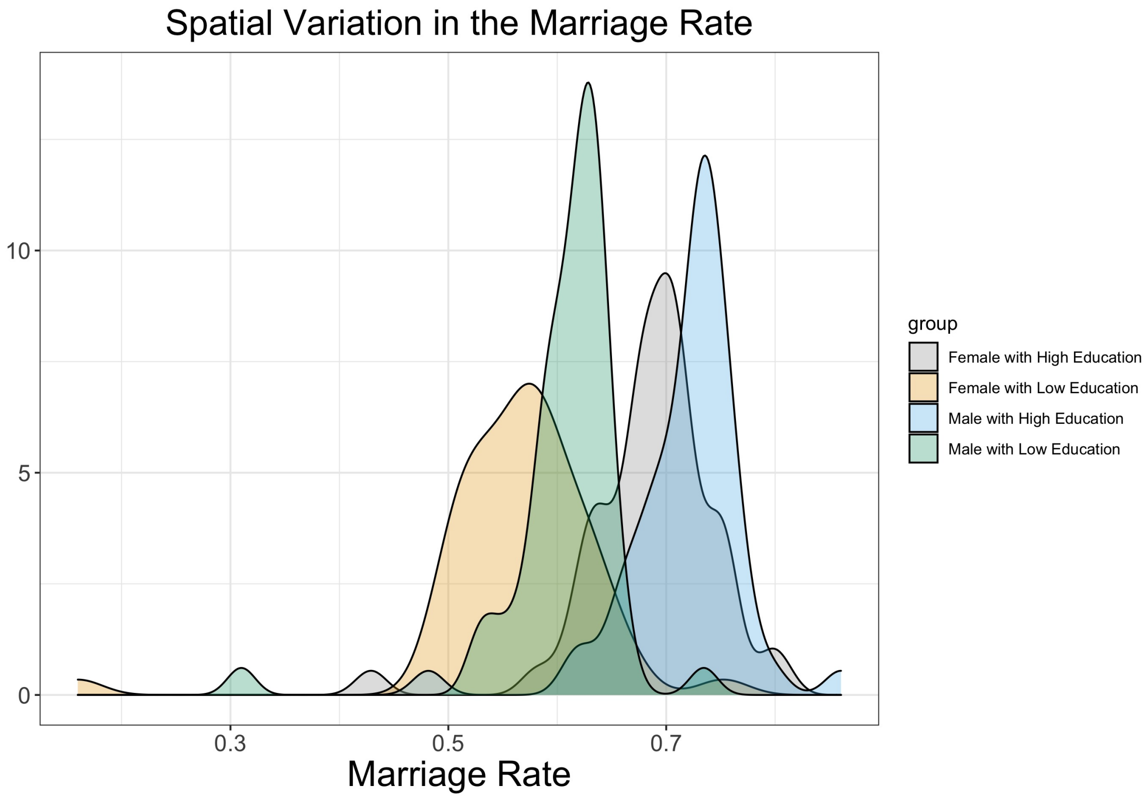
Notes: This figure plots state-level employment rate by gender and education group.

Figure 2: Spatial Variation in Log Mean Wage



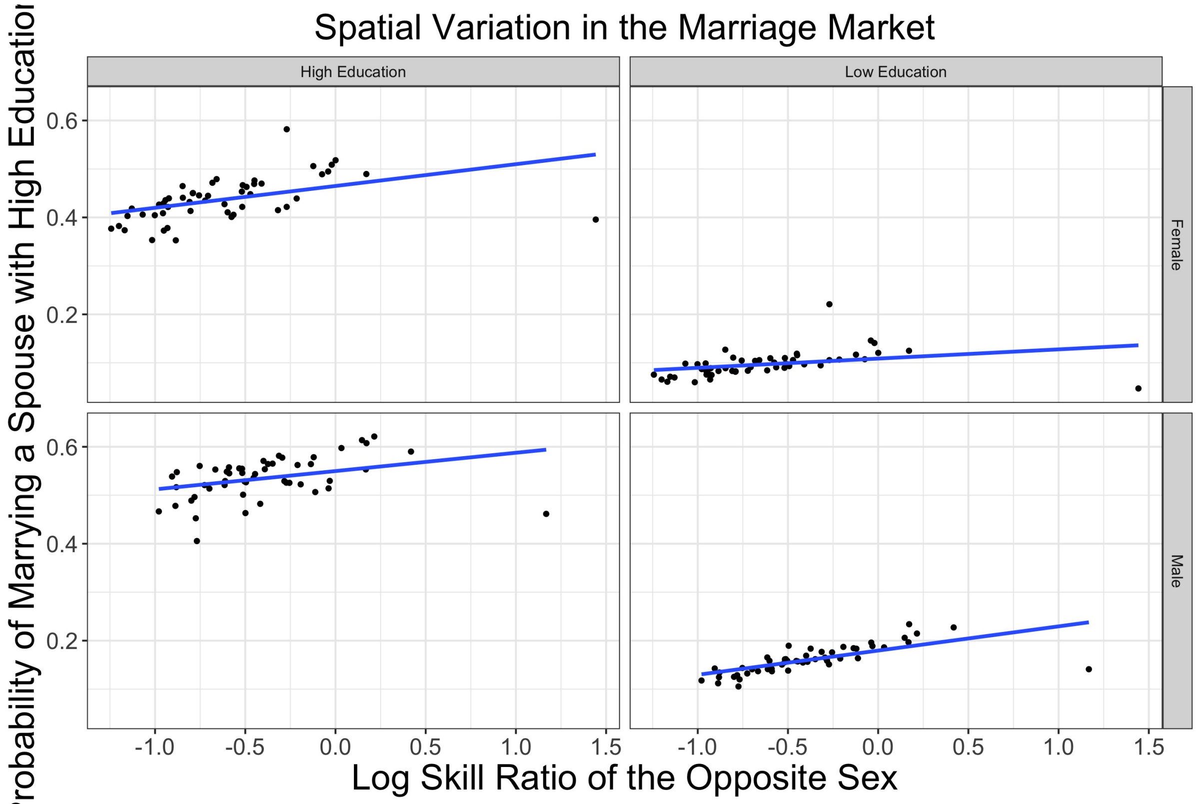
Notes: This figure plots state-level log mean wage by gender and education group.

Figure 3: Spatial Variation in Marriage Rate



Notes: This figure plots state-level marriage rate by gender and education group.

Figure 4: Spatial Variation in the Probability of Marrying a Highly-educated Spouse



Notes: Each point is a state. Each subgraph represents a scatterplot of the probability of marrying a spouse of high education level against the log skill ratio of the opposite sex. Skill ratio is defined as the ratio of the population with high education to the population with low education. The top-left one is for females with high education; the top-right one is for females with low education; the bottom-left one is for males with high education; and the bottom-right one is for males with low education.

Figure 5: A Roadmap of the Model

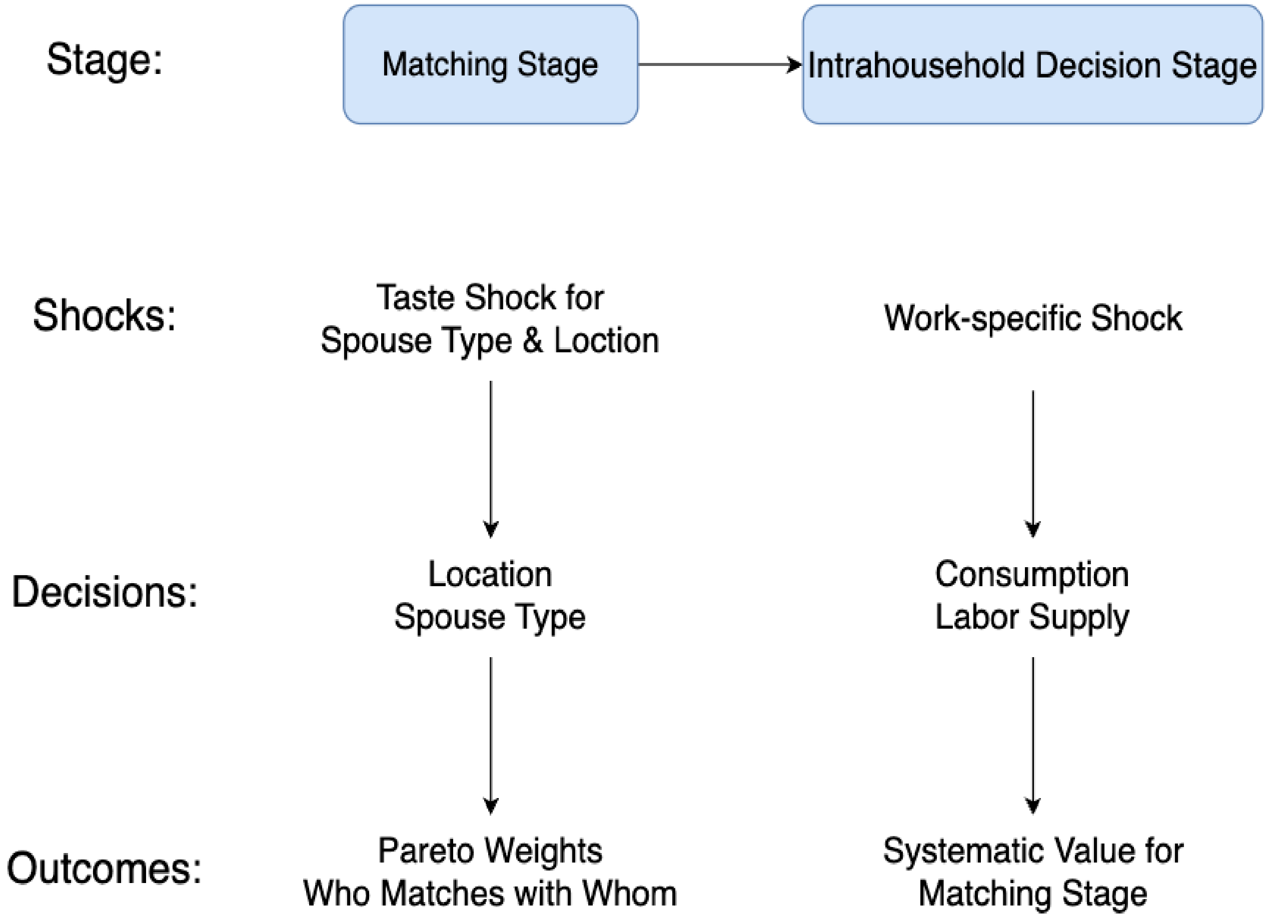


Figure 6: Mean Log Wage by Gender and Education (Working Full Time)

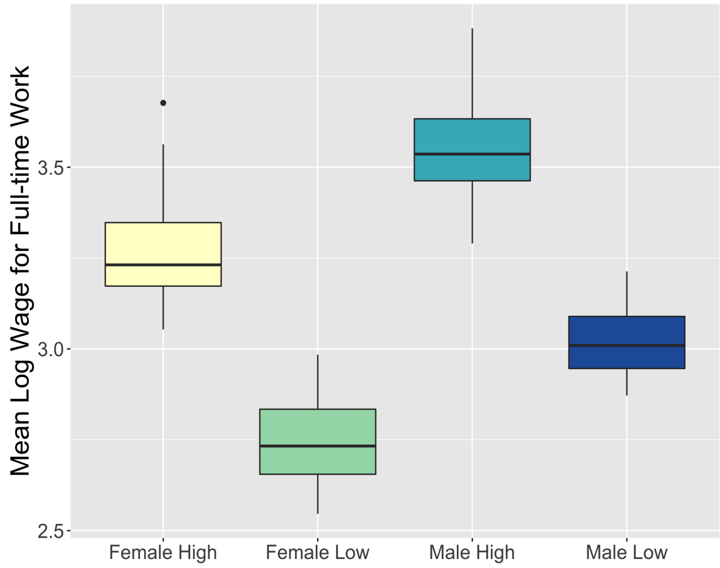


Figure 7: Part-time Penalty by Gender and Education

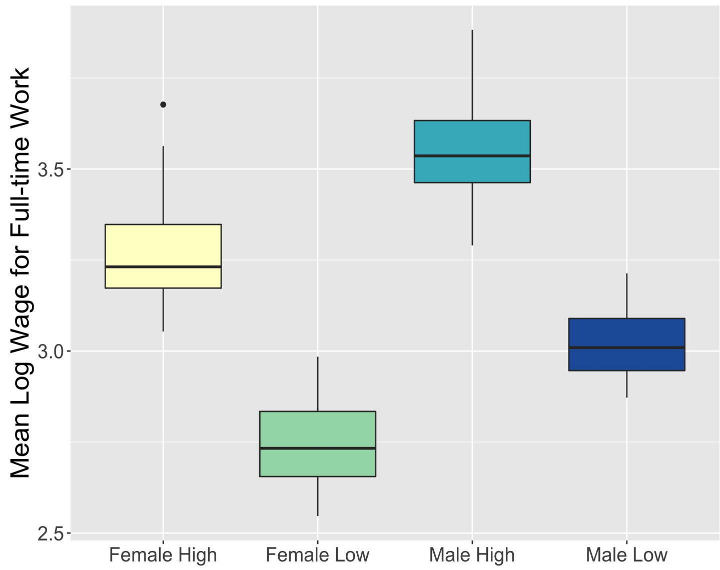
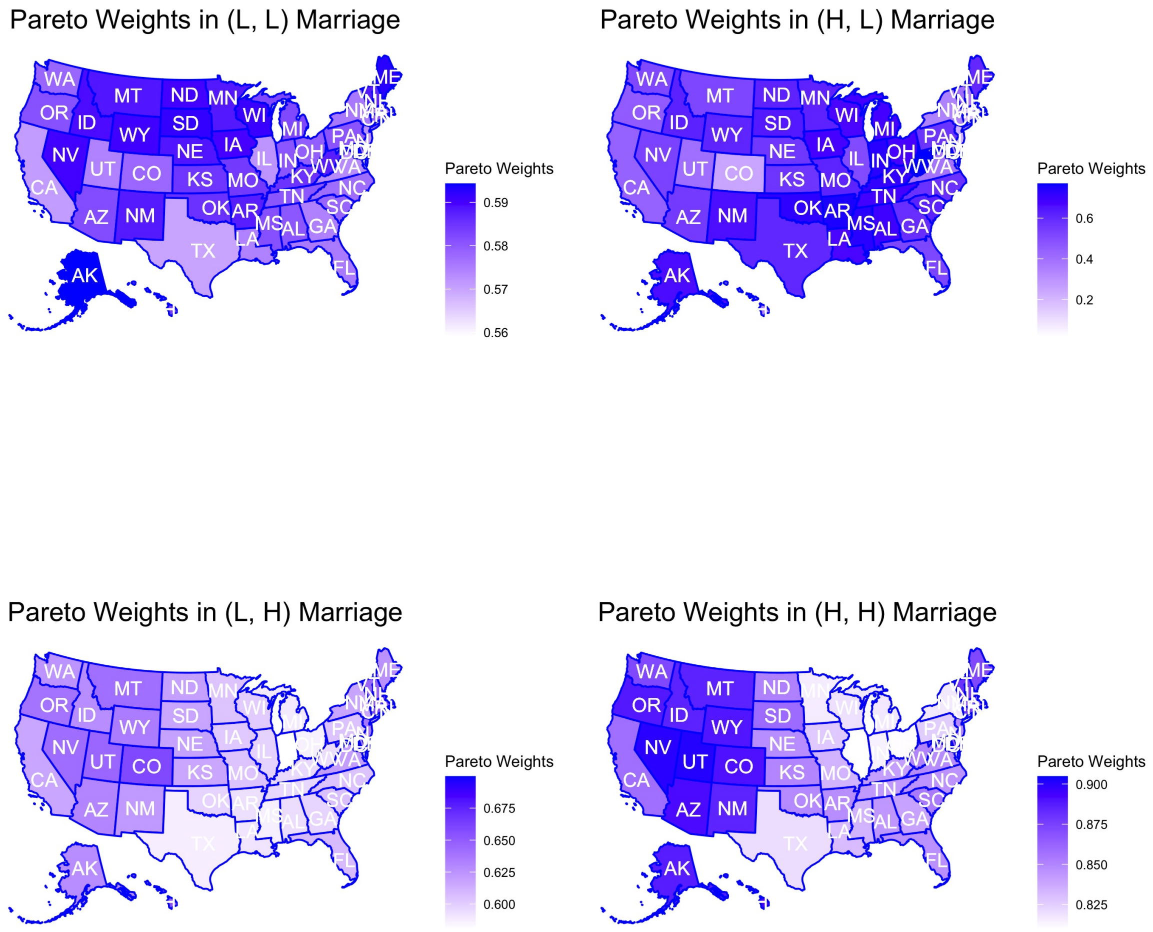
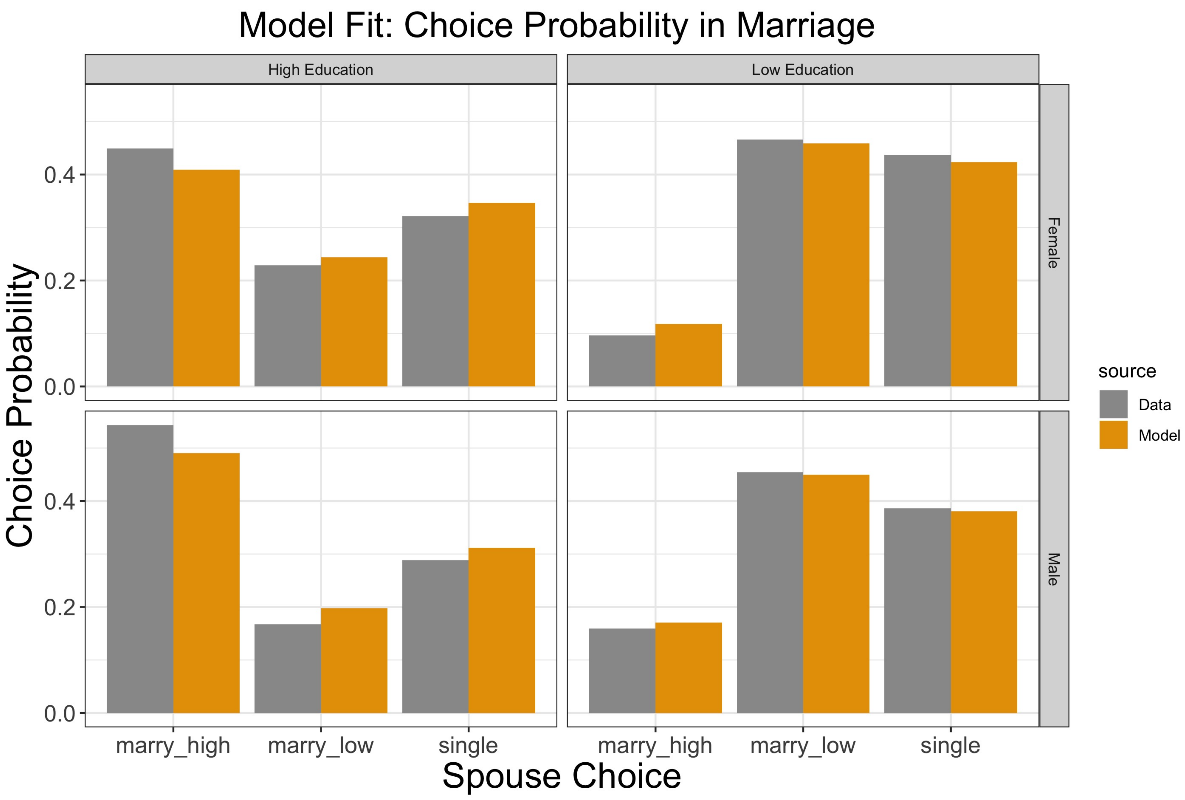


Figure 8: Pareto Weights by Matching Patterns



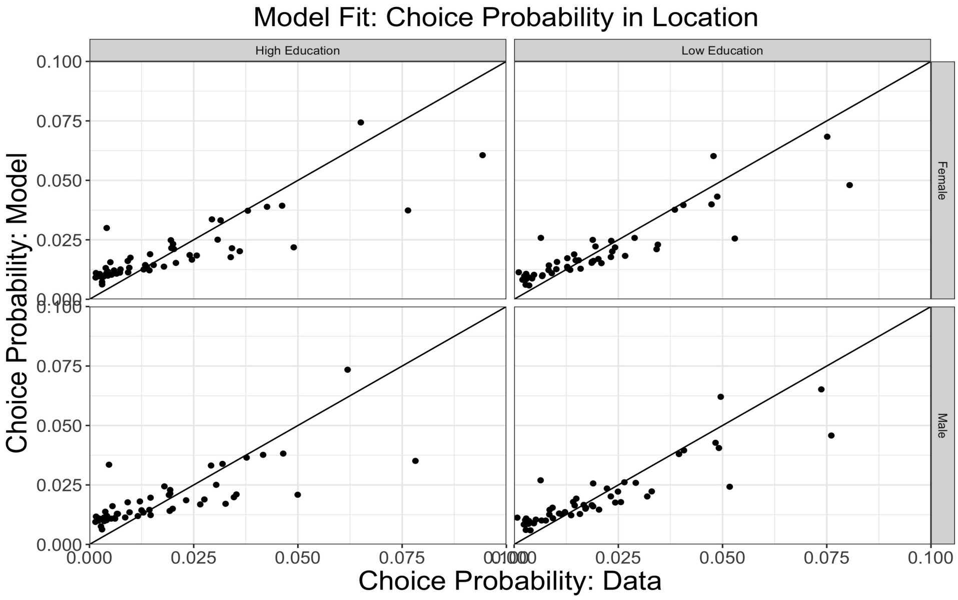
Notes: Each subgraph shows the spatial distribution of Pareto weights for a combination of marriages. The first letter in the bracket stands for the type of females while the second stands for males =.

Figure 9: Model Fit in Marriage Choices



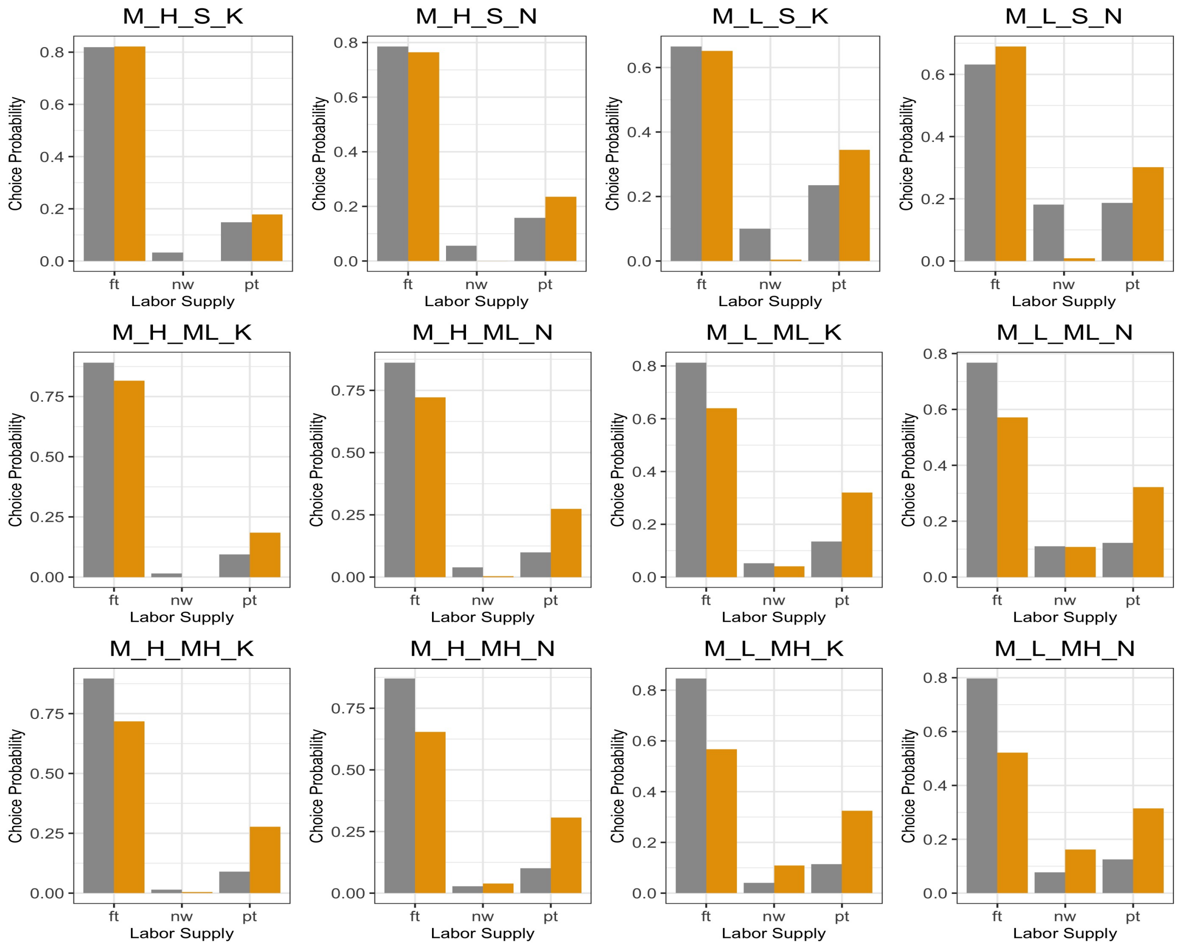
Notes: Each subgraph represents the marriage choice probabilities predicted by data and the model. The top-left one is for females with high education; the top-right one is for females with low education; the bottom-left one is for males with high education; and the bottom-right one is for males with low education.

Figure 10: Model Fit in Location Choices



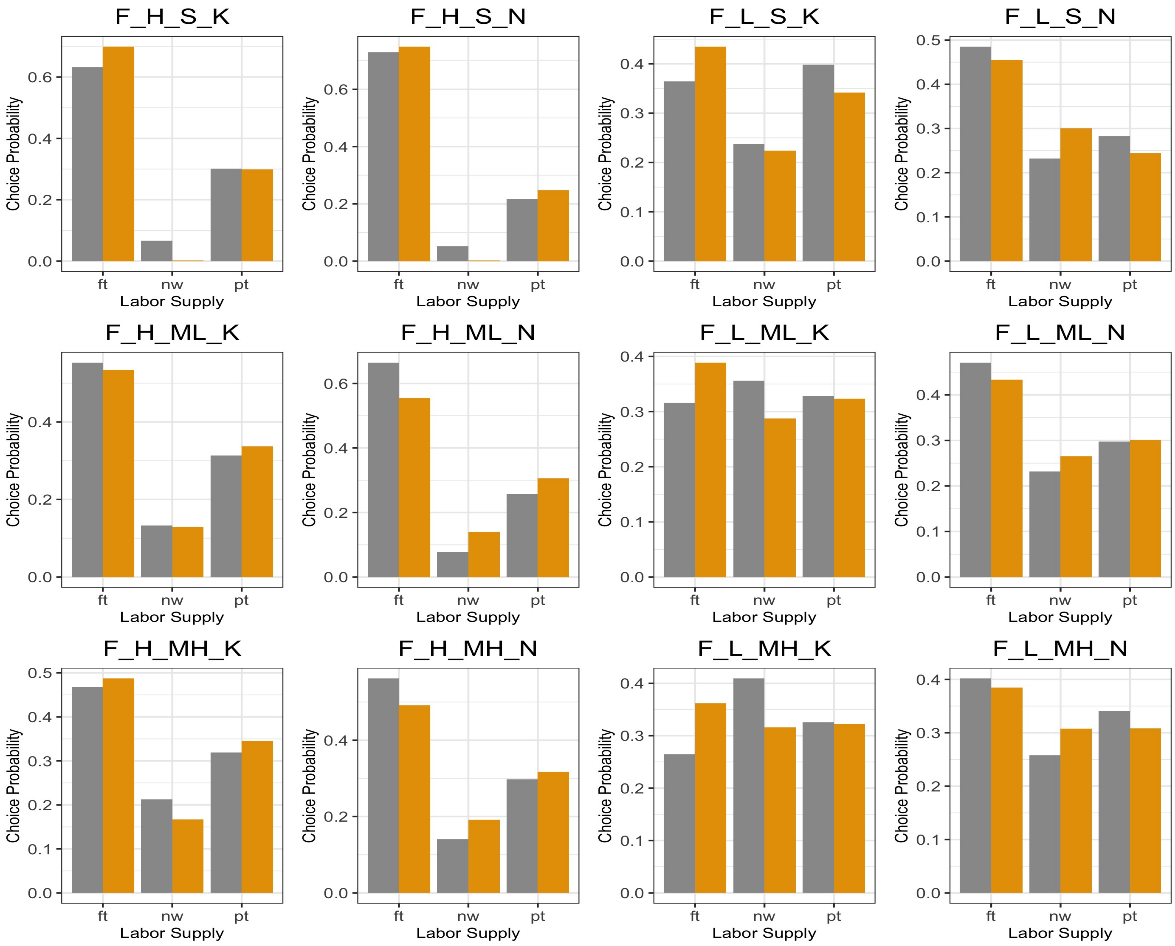
Notes: Each point is a state. Each subgraph represents a scatterplot of the probability of choosing a location. The x-axis represents the choice probabilities from the data; the y-axis represents the choice probabilities from the model predictions. The top-left one is for females with high education; the top-right one is for females with low education; the bottom-left one is for males with high education; and the bottom-right one is for males with low education.

Figure 11: Model Fit in Labor Supply for Males



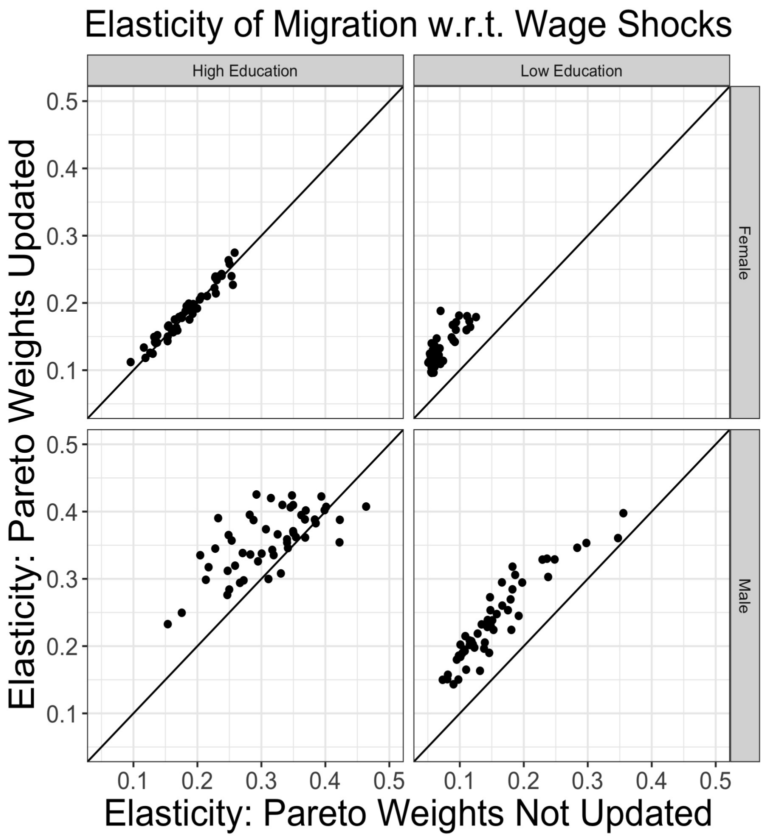
Notes: The Grey bar stands for data and the yellow bar stands for model prediction. 'M" stands for male, "F" stands for female, "H" stands for high education, "L" stands for low education, "S" stands for single, "ML" stands for marrying a lowly-educated spouse, "MH" stands for marrying a highly-educated spouse, "K" stands for having young kids, and "N" stands for having no young kids

Figure 12: Model Fit in Labor Supply for Females



*Notes:*The Grey bar stands for data and the yellow bar stands for model prediction. 'M" stands for male, "F" stands for female, "H" stands for high education, "L" stands for low education, "S" stands for single, "ML" stands for marrying a lowly-educated spouse, "MH" stands for marrying a highly-educated spouse, "K" stands for having young kids, and "N" stands for having no young kids

Figure 13: The Role of Marriage Market on Migration

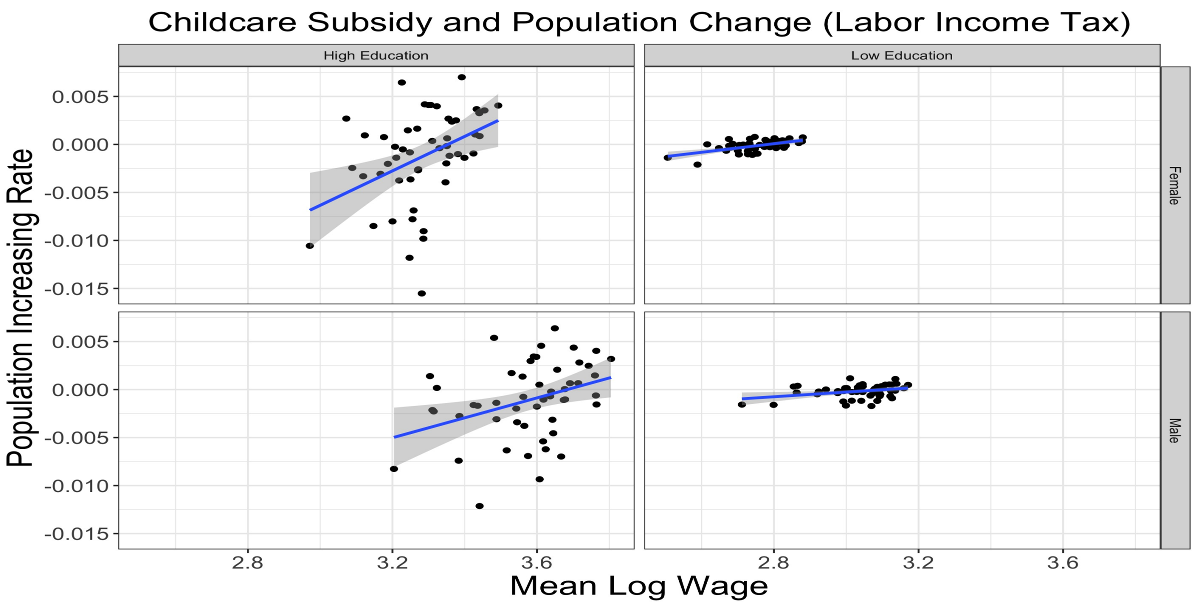


Notes: Each point is a state. Each subgraph represents a scatterplot of the elasticity of migration with respect to wage change for a demographic group defined by gender and education. The x-axis represents the elasticity holding Pareto weights fixed; the y-axis represents the elasticity where we update Pareto weights to clear all the marriage markets. The top-left one is for females with high education; the top-right one is for females with low education; the bottom-left one is for males with high education; and the bottom-right one is for males with low education.

Figure 14: 100% Childcare Subsidy and Population Change (Financed by Lump-sum Tax)

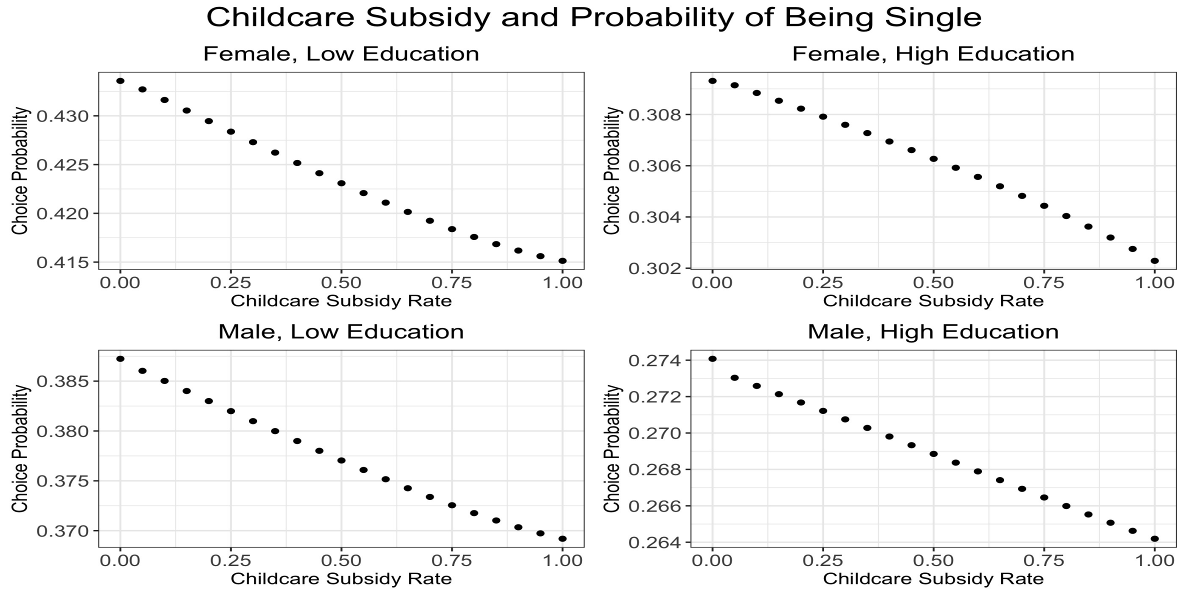
Notes: Each point is a state. Each subgraph represents a scatterplot of population increasing rate against log mean wage under a 100% childcare subsidy. A 100% childcare subsidy decreases childcare prices at each location to the lowest level in the data. The top-left one is for females with high education; the top-right one is for females with low education; the bottom-left one is for males with high education; and the bottom-right one is for males with low education.

Figure 15: 100% Childcare Subsidy and Population Change (Financed by Labor Income Tax)



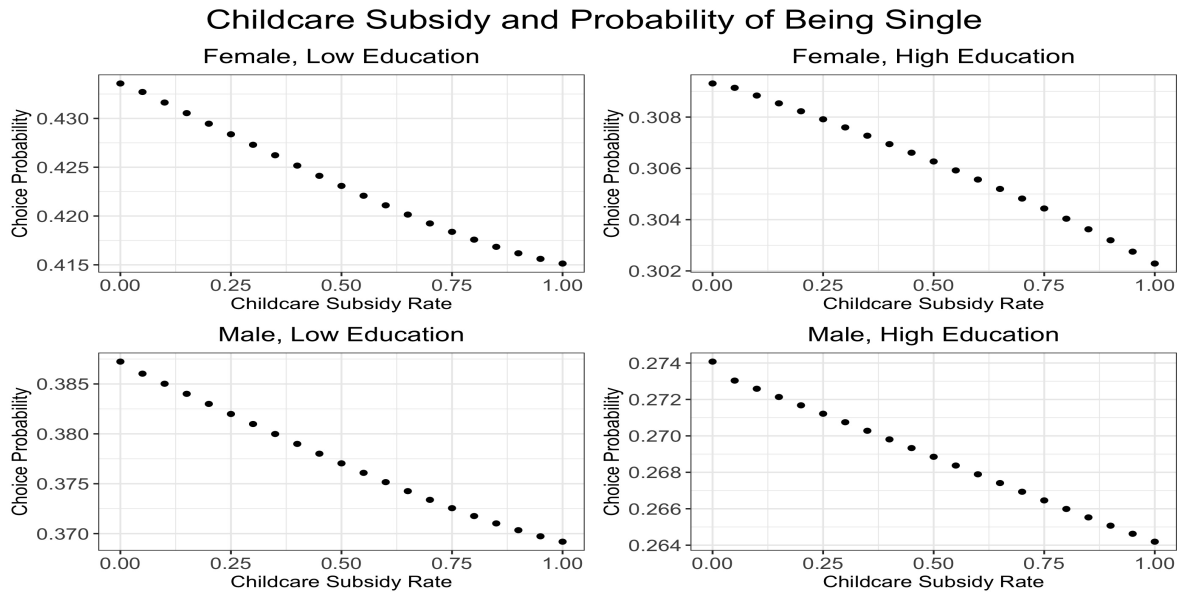
Notes: Each point is a state. Each subgraph represents a scatterplot of population increasing rate against log mean wage under a 100% childcare subsidy. A 100% childcare subsidy decreases childcare prices at each location to the lowest level in the data. The top-left one is for females with high education; the top-right one is for females with low education; the bottom-left one is for males with high education; and the bottom-right one is for males with low education.

Figure 16: Childcare Subsidy and Probability of Being Single (Financed by Lump-sum Tax)



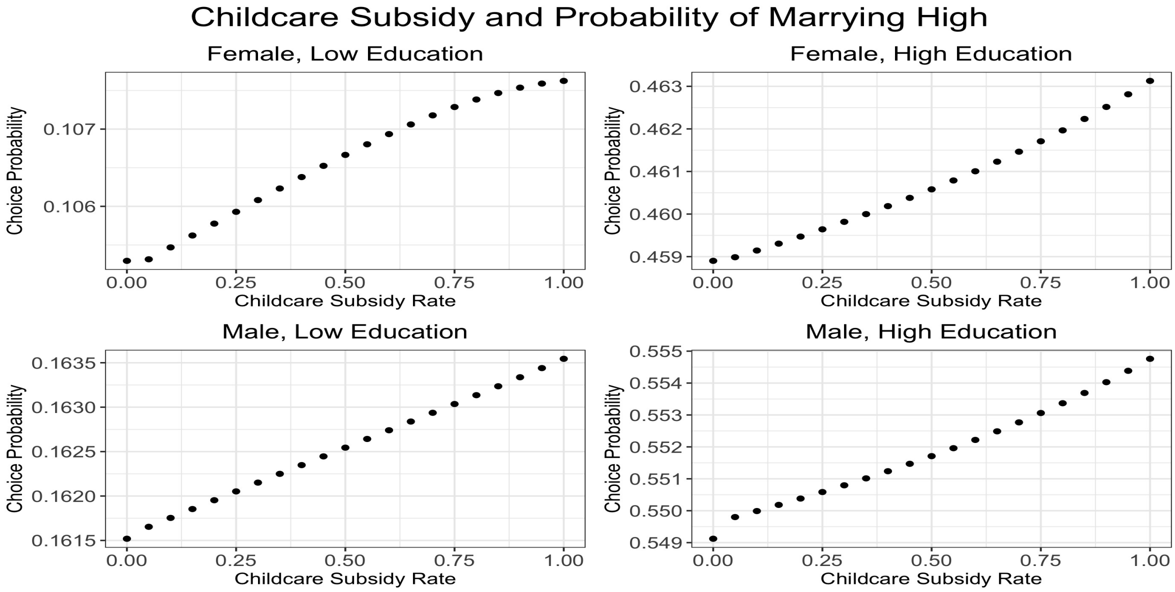
Notes: Each subgraph represents a scatterplot of the choice probability of being single against the childcare subsidy rate. The top-left one is for females with low education; the top-right one is for females with high education; the bottom-left one is for males with low education; and the bottom-right one is for males with high education.

Figure 17: Childcare Subsidy and Probability of Being Single (Financed by Labor Income Tax)



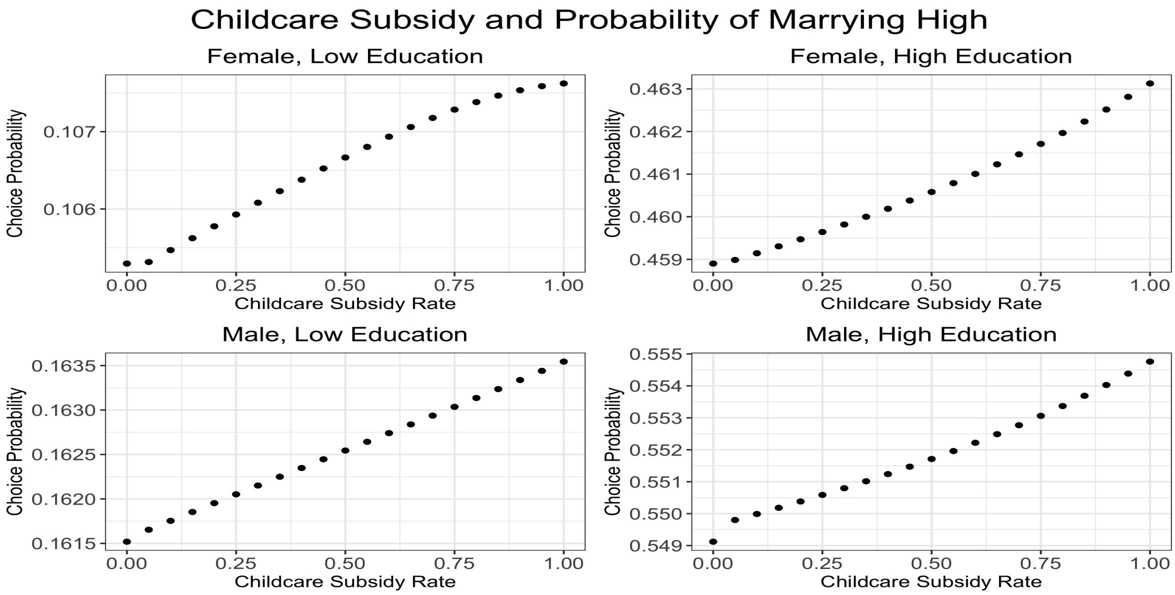
Notes: Each subgraph represents a scatterplot of the choice probability of being single against the childcare subsidy rate. The top-left one is for females with low education; the top-right one is for females with high education; the bottom-left one is for males with low education; and the bottom-right one is for males with high education.

Figure 18: Childcare Subsidy and Probability of Marrying High (Financed by Lump-sum Tax)



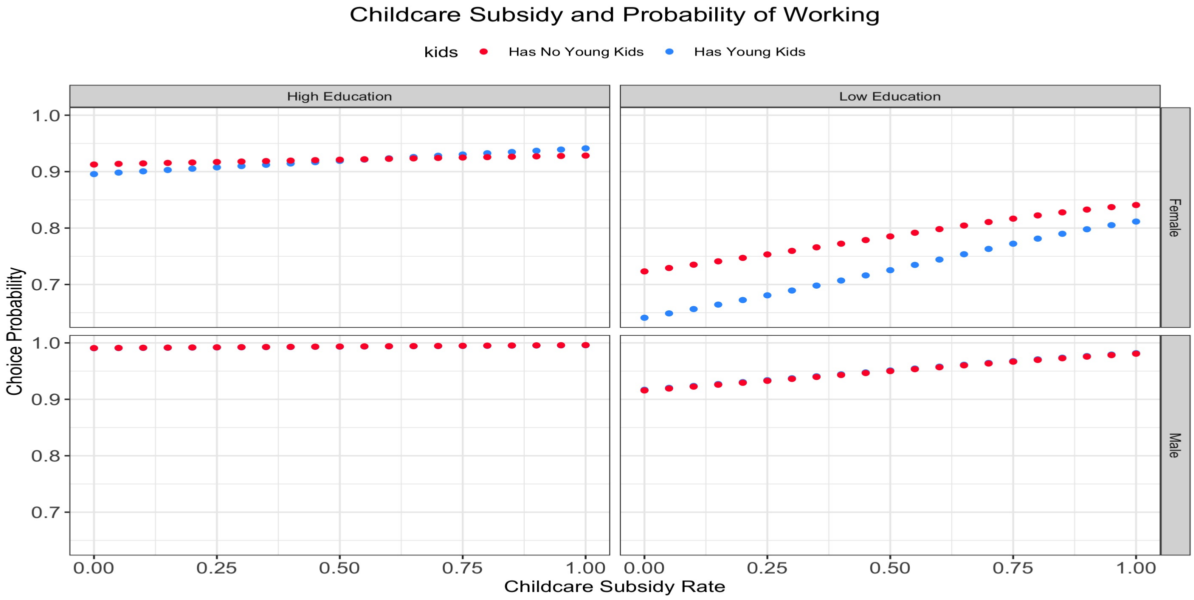
Notes: Each subgraph represents a scatterplot of the choice probability of marrying a highly-educated spouse against the childcare subsidy rate. The top-left one is for females with low education; the top-right one is for females with high education; the bottom-left one is for males with low education; and the bottom-right one is for males with high education.

Figure 19: Childcare Subsidy and Probability of Marrying High (Financed by Labor Income Tax)



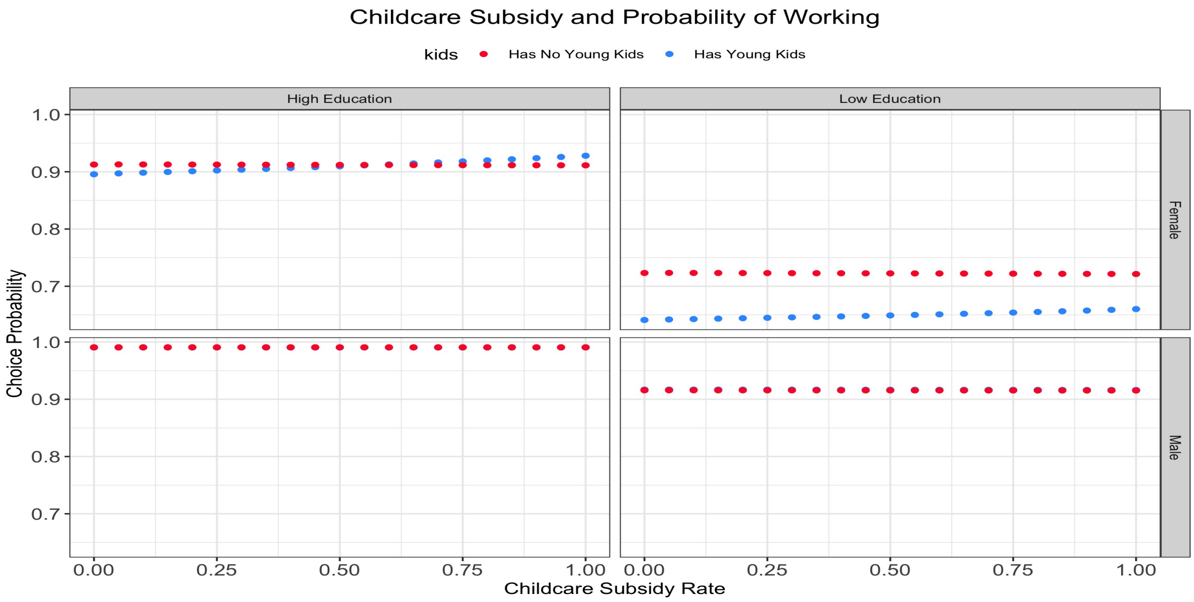
Notes: Each subgraph represents a scatterplot of the choice probability of marrying a highly-educated spouse against the childcare subsidy rate. The top-left one is for females with low education; the top-right one is for females with high education; the bottom-left one is for males with low education; and the bottom-right one is for males with high education.

Figure 20: Childcare Subsidy and Probability of Working (Financed by Lump-sum Tax)



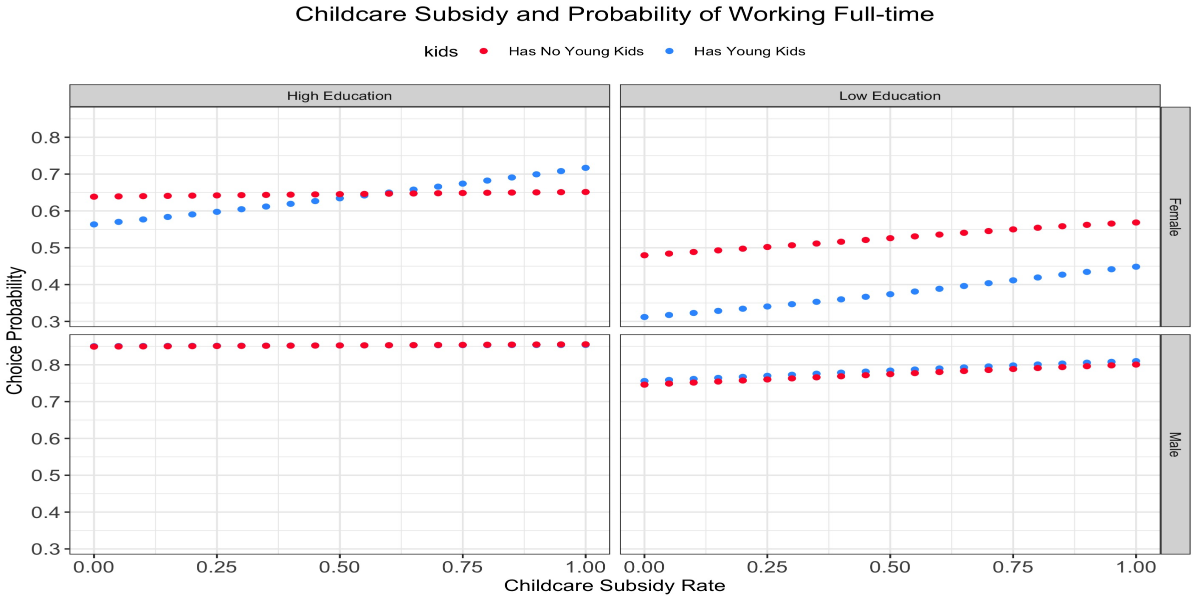
Notes: Each subgraph represents a scatterplot of the choice probability of Working against the childcare subsidy rate. The top-left one is for females with low education; the top-right one is for females with high education; the bottom-left one is for males with low education; and the bottom-right one is for males with high education.

Figure 21: Childcare Subsidy and Probability of Working (Financed by Labor Income Tax)



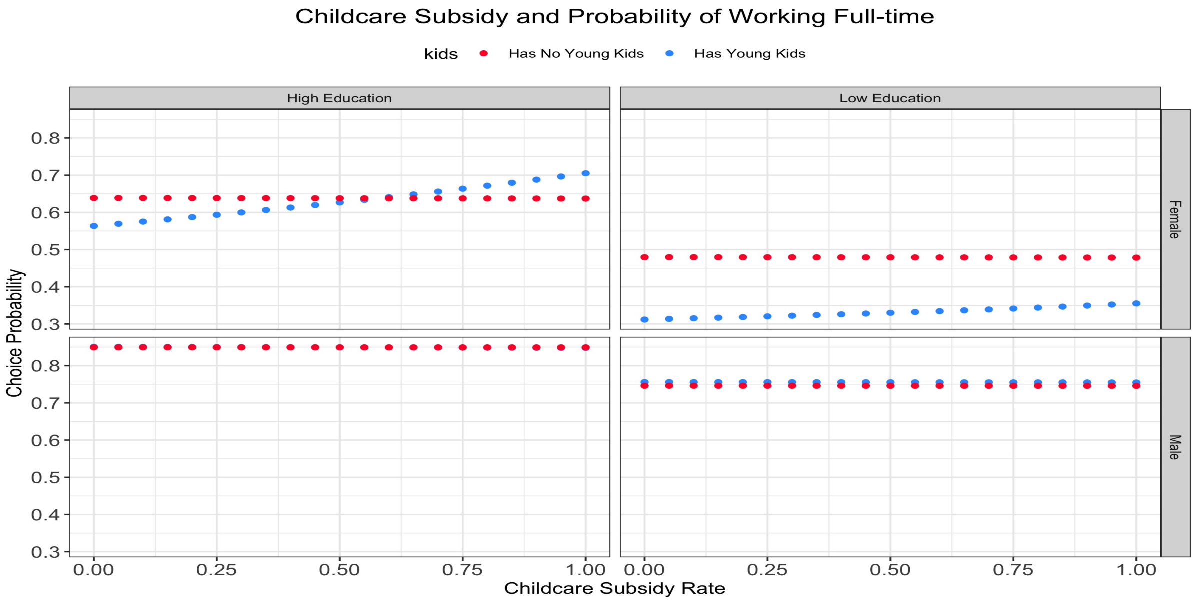
Notes: Each subgraph represents a scatterplot of the choice probability of working against the childcare subsidy rate. The top-left one is for females with low education; the top-right one is for females with high education; the bottom-left one is for males with low education; and the bottom-right one is for males with high education.

Figure 22: Childcare Subsidy and Probability of Working Full-time (Financed by Lump-sum Tax)



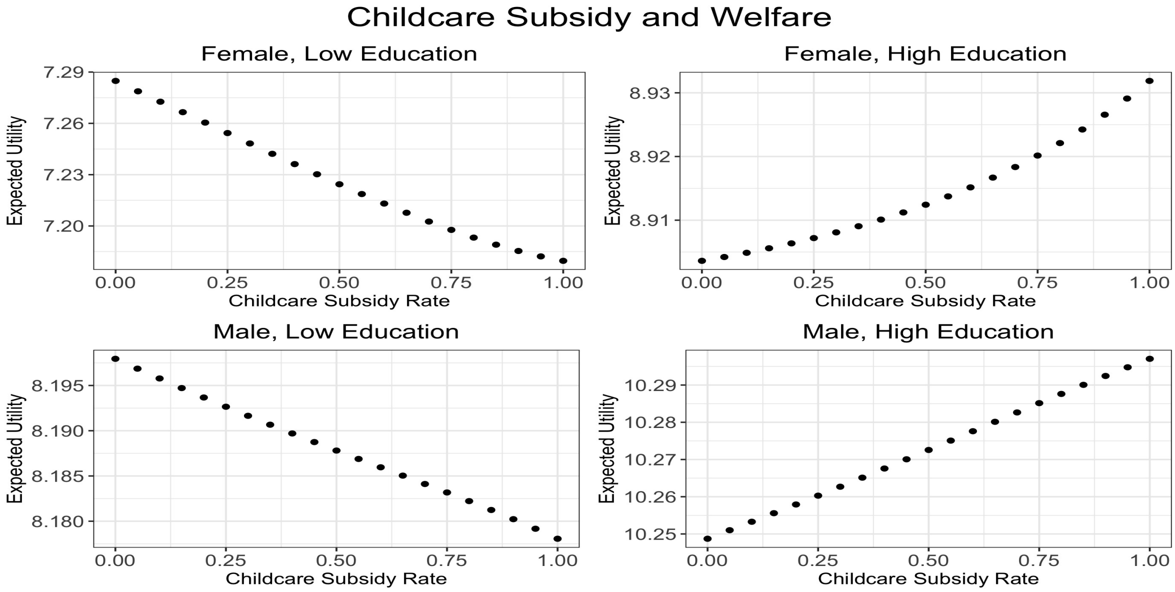
Notes: Each subgraph represents a scatterplot of the choice probability of working full-time against the childcare subsidy rate. The top-left one is for females with low education; the top-right one is for females with high education; the bottom-left one is for males with low education; and the bottom-right one is for males with high education.

Figure 23: Childcare Subsidy and Probability of Working Full-time (Financed by Labor Income Tax)



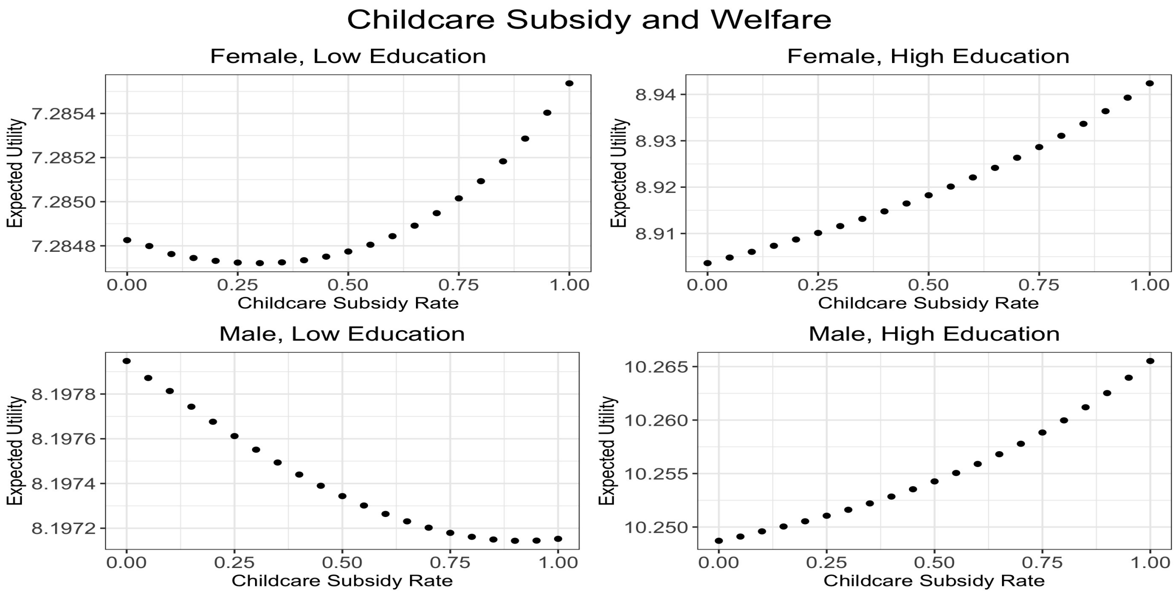
Notes: Each subgraph represents a scatterplot of the choice probability of working full-time against the childcare subsidy rate. The top-left one is for females with low education; the top-right one is for females with high education; the bottom-left one is for males with low education; and the bottom-right one is for males with high education.

Figure 24: Childcare Subsidy and Welfare (Financed by Lump-sum Tax)



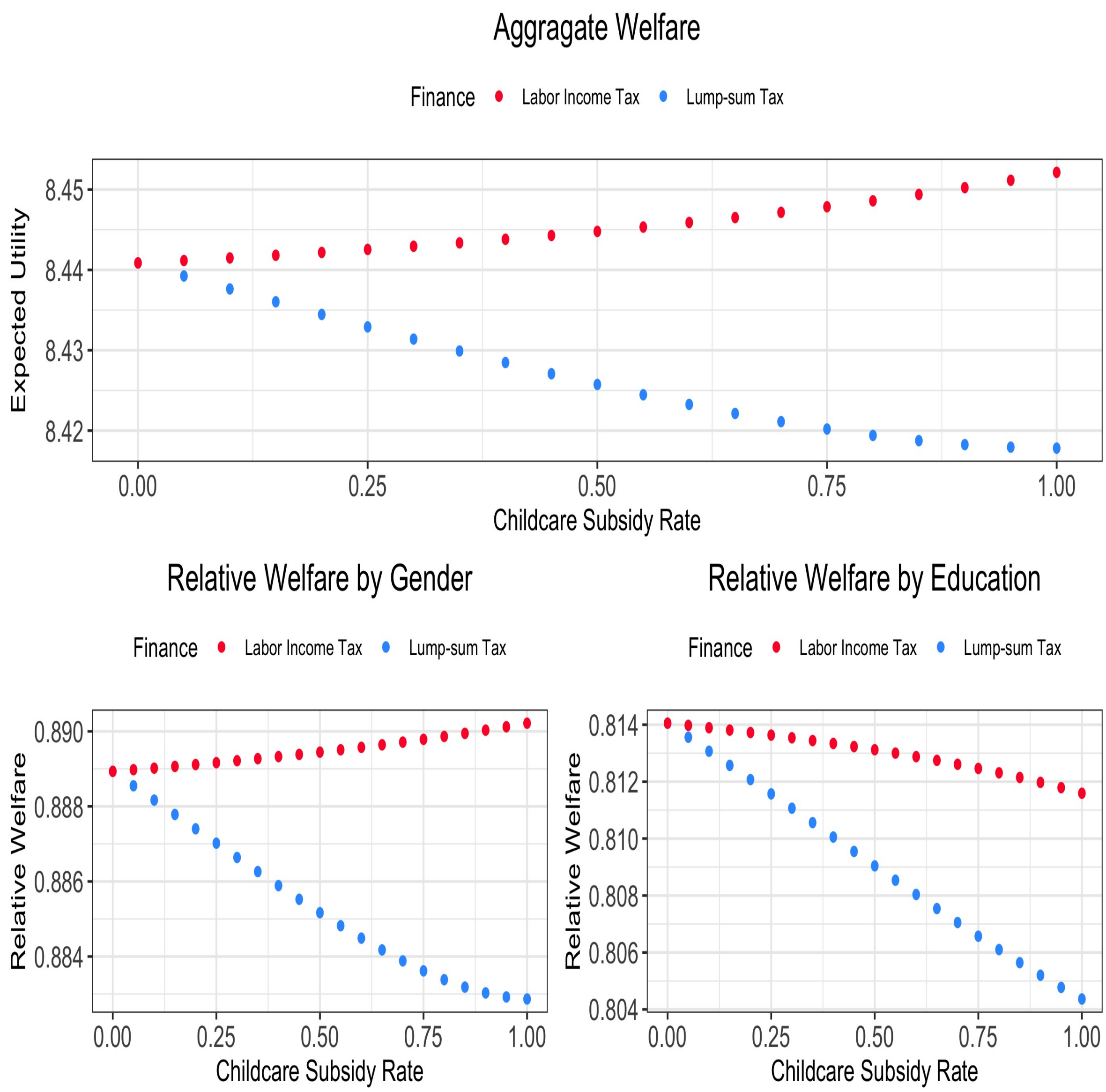
Notes: Each subgraph represents a scatterplot of the expected utility against the childcare subsidy rate. The top-left one is for females with low education; the top-right one is for females with high education; the bottom-left one is for males with low education; and the bottom-right one is for males with high education.

Figure 25: Childcare Subsidy and Welfare (Financed by Labor Income Tax)



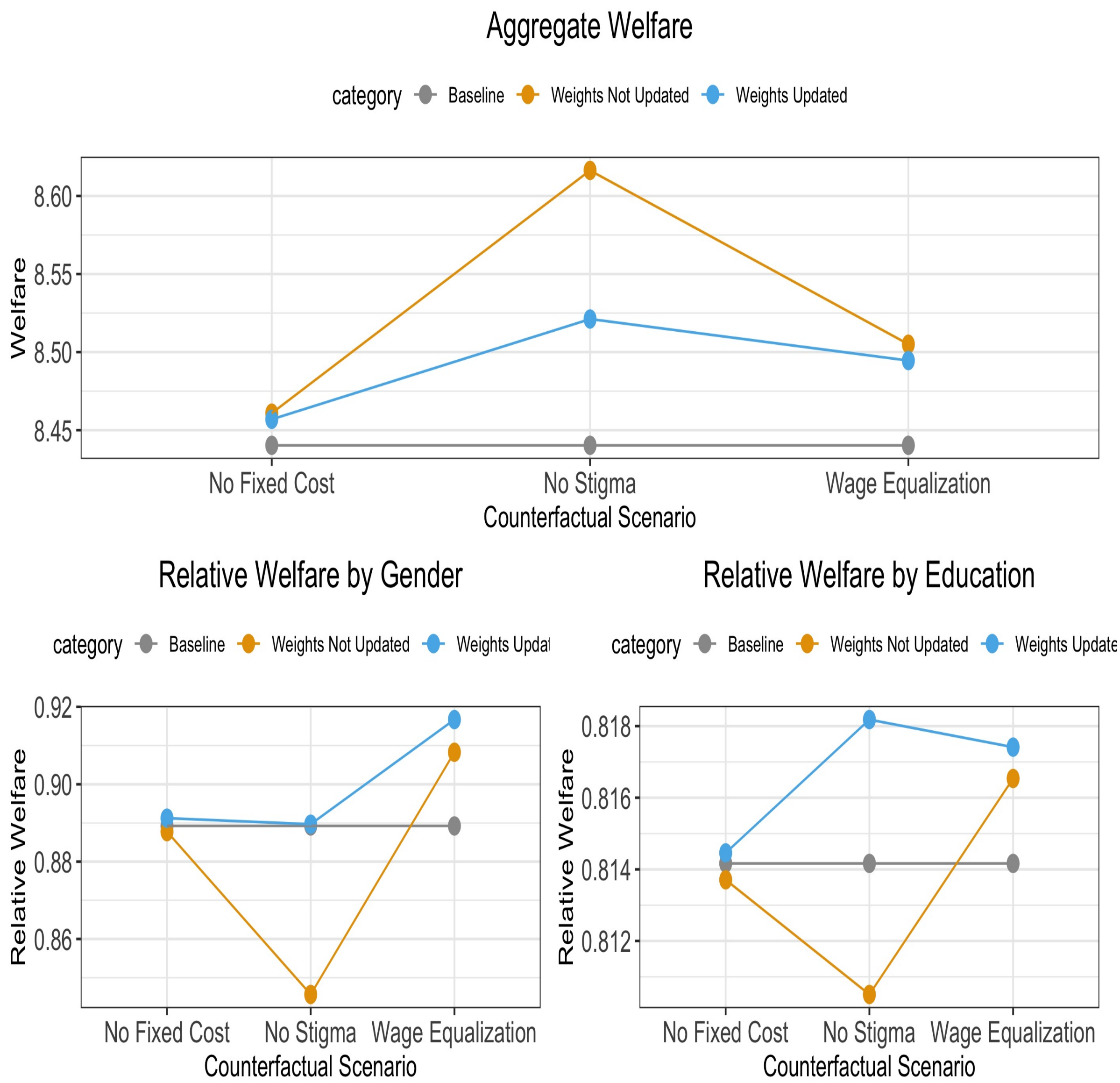
Notes: Each subgraph represents a scatterplot of the expected utility against the childcare subsidy rate. The top-left one is for females with low education; the top-right one is for females with high education; the bottom-left one is for males with low education; and the bottom-right one is for males with high education.

Figure 26: Childcare Subsidy and Aggregate Welfare



Notes: The three subgraph represents a scatterplot of aggregate welfare, gender welfare gap, and education welfare gap against the childcare subsidy rate.

Figure 27: Welfare Analysis Under Three Scenarios



Notes: The graphs show the aggregate welfare, gender welfare gap, and education welfare gap under three counterfactual scenarios. “No Fixed Cost” means females face no fixed cost of working full-time; ”No Stigma” means husbands won’t incur a stigma in utility if their earning is lower than their wife; “Wage Equalization” means that the females face the same wage offers as males of the same education level.

B Identification

B.1 Identification of Pareto Weights

Consider a (e_f, e_m) marriage at location s. We write out the demand (number of women of type e_f who choose to marry men of type e_m at location s) as below:

$$\mu^f_{e_f e_m s} = \Sigma_{bs} P^f_{e_f e_m s}(bs) \times POP_{e_f}(bs) \tag{33}$$

where $\mu^f_{e_f e_m s}$ is the number of women of type e_f who choose to marry men of type e_m at location s, bs denotes birth state, $P^f_{e_f e_m s}(bs)$ is the choice probability of women of type e_f whose birth state is bs, and $POP_{e_f}(bs)$ is the number of women of type e_f whose birth state is bs. To prove identification, we rewrite the demand as:

$$\begin{aligned}
\mu^f_{e_f e_m s} &= \Sigma_{bs} P^f_{e_f e_m s}(bs) \times POP_{e_f}(bs) \\
&= \Sigma_{bs} \frac{P^f_{e_f e_m s}(bs)}{P^f_{e_f 0 s}(bs)} \times (POP_{e_f}(bs) \times P^f_{e_f 0 s}(bs)) \\
&= \Sigma_{bs} e^{\frac{V^f_{e_f e_m s}(\lambda_{e_f e_m s}) - V^f_{e_f 0 s}}{\sigma^{ma}}} \times (POP_{e_f}(bs) \times P^f_{e_f 0 s}(bs)) \\
&= e^{\frac{V^f_{e_f e_m s}(\lambda_{e_f e_m s}) - V^f_{e_f 0 s}}{\sigma^{ma}}} \times \Sigma_{bs} POP_{e_f}(bs) \times P^f_{e_f 0 s}(bs) \\
&= e^{\frac{V^f_{e_f e_m s}(\lambda_{e_f e_m s}) - V^f_{e_f 0 s}}{\sigma^{ma}}} \times \mu^f_{e_f 0 s}
\end{aligned} \tag{34}$$

where $\mu^f_{e_f 0 s}$ is the number of women of type e_f who choose to stay single at location s. Take the log of both sides, we get:

$$log\mu^f_{e_f e_m s}(\Lambda) - log\mu^f_{e_f 0 s}(\Lambda_{e_f \cdot\cdot}) = \frac{V^f_{e_f e_m s}(\lambda_{e_f e_m s}) - V^f_{e_f 0 s}}{\sigma^{ma}} \tag{35}$$

Symmetrically, we can write the log supply equation as:

$$log\mu^m_{e_f e_m s}(\Lambda) - log\mu^m_{0 e_m s}(\Lambda_{\cdot e_m \cdot}) = \frac{V^m_{e_f e_m s}(\lambda_{e_f e_m s}) - V^m_{0 e_m s}}{\sigma^{ma}} \tag{36}$$

We put the equilibrium constraint, then:

$$log\mu^f_{e_f e_m s}(\Lambda) = log\mu^m_{e_f e_m s}(\Lambda) = log\mu_{e_f e_m s}(\Lambda) \tag{37}$$

With equations (35) and (36), now we can prove identification following the argument in Gayle and Shephard (2019). Consider some factors that only affect the expected value of marriage through its impact on the Pareto weights: these are called "distribution factors" (see Bourguignon, Browning and Chiappori (2009)). In our model, variables in the amenity term play the role of distribution factors because they don't affect the expected value of marriage but they affect people's choice probability of each location, thus affecting the supply and demand in the marriage market[12]. Consider a perturbation of any distribution factor Δ across locations, we get:

$$\Sigma_k \frac{\partial(log\mu^f_{e_f e_m s}(\Lambda) - log\mu^f_{e_f 0 s}(\Lambda_{e_f \cdot\cdot}))}{\partial\Delta_k} \cdot d\Delta_k = \frac{1}{\sigma^{ma}} \cdot \frac{\partial V^f_{e_f e_m s}(\lambda_{e_f e_m s})}{\partial\lambda_{e_f e_m s}} \Sigma_k \frac{\partial\lambda_{e_f e_m s}}{\partial\Delta_k} \cdot d\Delta_k \tag{38}$$

$$\Sigma_k \frac{\partial(log\mu^m_{e_f e_m s}(\Lambda) - log\mu^m_{0 e_m s}(\Lambda_{\cdot e_m \cdot}))}{\partial\Delta_k} \cdot d\Delta_k = \frac{1}{\sigma^{ma}} \cdot \frac{\partial V^m_{e_f e_m s}(\lambda_{e_f e_m s})}{\partial\lambda_{e_f e_m s}} \Sigma_k \frac{\partial\lambda_{e_f e_m s}}{\partial\Delta_k} \cdot d\Delta_k \tag{39}$$

Divide equation (38) by equation (39), we obtain:

$$\frac{\Sigma_k \frac{\partial(log\mu^f_{e_f e_m s}(\Lambda) - log\mu^f_{e_f 0 s}(\Lambda_{e_f \cdot\cdot}))}{\partial\Delta_k} \cdot d\Delta_k}{\Sigma_k \frac{\partial(log\mu^m_{e_f e_m s}(\Lambda) - log\mu^m_{0 e_m s}(\Lambda_{\cdot e_m \cdot}))}{\partial\Delta_k} \cdot d\Delta_k} = \frac{\frac{\partial V^f_{e_f e_m s}(\lambda_{e_f e_m s})}{\partial\lambda_{e_f e_m s}}}{\frac{\partial V^m_{e_f e_m s}(\lambda_{e_f e_m s})}{\partial\lambda_{e_f e_m s}}} \tag{40}$$

The left-hand side of equation (40) can be directly estimated from the data, now we consider the right-hand side. By the Envelop Theorem, we have:

$$V^f_{e_f e_m s}(\lambda_{e_f e_m s}) + \lambda_{e_f e_m s} \frac{\partial V^f_{e_f e_m s}(\lambda_{e_f e_m s})}{\partial\lambda_{e_f e_m s}} - V^m_{e_f e_m s}(\lambda_{e_f e_m s}) + (1 - \lambda_{e_f e_m s}) \frac{\partial V^m_{e_f e_m s}(\lambda_{e_f e_m s})}{\partial\lambda_{e_f e_m s}} = \left. \frac{\partial[\lambda_{e_f e_m s} u_f(c_f, l_f, h) + (1 - \lambda_{e_f e_m s}) u_m(c_m, l_m, h)]}{\partial\lambda_{e_f e_m s}} \right|_{c,\ l,\ h \text{ are optimal}}, \tag{41}$$

[12] Actually we have to assume that the distribution factor affects men and women differently so relative magnitude of supply to demand can be affected. In our estimation, we find the amenity parameters for women and men differ. So this assumption is supported by the data.

where we suppress variables other than the Pareto weights to reduce clutter. Simplify the above equation, we have:

$$\frac{\frac{\partial V^f_{e_f e_m s}(\lambda_{e_f e_m s})}{\partial \lambda_{e_f e_m s}}}{\frac{\partial V^m_{e_f e_m s}(\lambda_{e_f e_m s})}{\partial \lambda_{e_f e_m s}}} = -\frac{1-\lambda_{e_f e_m s}}{\lambda_{e_f e_m s}} \tag{42}$$

Combine equation (40) and (42), we can identify the Pareto weight as below:

$$\frac{1-\lambda_{e_f e_m s}}{\lambda_{e_f e_m s}} = -\frac{\Sigma_k \frac{\partial(log\mu^f_{e_f e_m s}(\Lambda) - log\mu^f_{e_f 0 s}(\Lambda_{e_f \cdot\cdot}))}{\partial \Delta_k} \cdot d\Delta_k}{\Sigma_k \frac{\partial(log\mu^m_{e_f e_m s}(\Lambda) - log\mu^m_{0 e_m s}(\Lambda_{\cdot e_m \cdot}))}{\partial \Delta_k} \cdot d\Delta_k} \tag{43}$$

Thus we have established the identification of the Pareto weights.

B.2 Identification of Labor Supply Parameters

Since we assume that marital status doesn't affect preference for consumption and leisure, we can identify parameters regarding labor supply decisions just by observing single people's labor supply choices. We allow those parameters to vary by gender and education, so here we show identification using a generic female. We write out the latent utility associated with full-time work, part-time work, and not working as below:

$$\begin{aligned} u(NW) &= ln(N) \\ u(PT) &= ln(N+0.5w) - 0.5\theta^{ls} \\ u(FT) &= ln(N+w) - \theta^{ls} \end{aligned} \tag{44}$$

Then we can write out the log relative probability of working full-time to part-time conditional on wage as:

$$ln\frac{p(FT|w)}{p(PT|w)} = \frac{1}{\sigma^{ls}} ln\frac{(N+w)}{(N+0.5w)} - 0.5\frac{\theta^{ls}}{\sigma^{ls}} \tag{45}$$

Take the partial derivative with respect to wage, the variation in wage will identify σ^{ls}. Now we integrate any probability in (44) with respect to wage, it will only be a function of θ^{ls}. By observing the proportion of people in each working status, we identify θ^{ls}.

B.3 Identification of Other Parameters

Now we discuss how we identify parameters associated with cost from migration (θ^{bs}), utility from local amenity (θ^{a}), utility from local skill ratio (θ^{skill}), match quality (θ^{match}), dispersion of marital shock (θ^{ma}). Consider two women who were born in the same state and have the same level of education, they both choose to be single but one chooses to stay at the birth state while another chooses to migrate out, we write out the log relative choice probability as below:

$$log\frac{p^{f}_{e_f0s}(bs=s)}{p^{f}_{e_f0s'}(bs=s)}=\frac{v^{f}_{e_f0s}-v^{f}_{e_f0s'}+\theta^{a}_{e_f}(a_s-a_{s'})+\theta^{skill}_{e_f}(skill_s-skill_{s'})+\theta^{bs}_{e_f}}{\sigma^{ma}} \tag{46}$$

Since we have identified all the parameters that enter the expected value of single people, $v^{f}_{e_f0s}-v^{f}_{e_f0s'}$ is known. As long as there is variation in $v^{f}_{e_f0s}-v^{f}_{e_f0s'}$, $a_s-a_{s'}$, and $skill_s-skill_{s'}$ among different pairs of s and s', we can identify σ^{ma}, $\frac{\theta^{a}_{e_f}}{\sigma^{ma}}$, and $\frac{\theta^{skill}_{e_f}}{\sigma^{ma}}$. Since the data have enough variation in wages and amenities across locations, we can identify σ^{ma}, $\theta^{a}_{e_f}$ and $\theta^{skill}_{e_f}$.

Consider the below equation:

$$log\frac{p^{f}_{e_f0s'}(bs=s')}{p^{f}_{e_f0s}(bs=s')}=\frac{v^{f}_{e_f0s'}-v^{f}_{e_f0s}+\theta^{a}_{e_f}(a_{s'}-a_s)+\theta^{skill}_{e_f}(skill_{s'}-skill_s)+\theta^{bs}_{e_f}}{\sigma^{ma}} \tag{47}$$

Adding up equations (46) and (47), we can identify $\theta^{bs}_{e_f}$ as:

$$\theta^{bs}_{e_f}=\frac{\sigma^{ma}}{2}(log\frac{p^{f}_{e_f0s}(bs=s)}{p^{f}_{e_f0s'}(bs=s)}+log\frac{p^{f}_{e_f0s'}(bs=s')}{p^{f}_{e_f0s}(bs=s')}) \tag{48}$$

Last, we show the identification of θ^{match}, consider the below log relative choice probability:

$$log\frac{p^{f}_{e_fe_ms}(bs=s)}{p^{f}_{e_f0s}(bs=s)}=\frac{v^{f}_{e_fe_ms}-v^{f}_{e_f0s}}{\sigma^{ma}} \tag{49}$$

In the above equation, the only thing unknown is the match quality parameter, which enters through $v^{f}_{e_fe_ms}$. So by matching the above equation to the observed log relative choice probability for $e_m=e_f$, $e_m<e_f$ and $e_m>e_f$ respectively, we can back out θ^{match}_0, θ^{match}_1 and θ^{match}_2. Now we have identified all the structural parameters.

C Estimating Moments

In this Appendix, we describe the moments we target. Inspired by the identification proof, we choose moments that relate closely to location choices, marital choices, and labor supply. We have chosen five sets of moments:

The first set of moments relates to location choice. For each gender and education level, we compute the choice frequency of location (204 moments).

The second set of moments relates to marital decisions: for each gender, and education level, we compute the choice frequency of each marital status (12 moments).

The third set of moments targets migration decisions. For each gender, education level, and birth state, we compute the choice frequency of leaving outside of the birth state (204 moments).

The fourth set of moments targets the labor supply decisions of single people. For each gender, education level, location, and the presence of young kids, we compute the choice frequencies of part-time and full-time work (800 moments).

The fifth set of moments targets the labor supply of married people. For each gender, education level, marital status, and the presence of young kids, we compute the frequencies of labor supply (36 moments).

In total, we have 1252 moments.